A paired neural network model for tourist arrival forecasting

Abstract

Tourist arrival and tourist demand forecasting are a crucial issue in tourism economy and the community economic development as well. Tourist demand forecasting has attracted much attention from tourism academics as well as industries. In recent year, it attracts increasing attention in the computational literature as advances in machine learning method allow us to construct models that significantly improve the precision of tourism prediction. In this paper, we draw upon both strands of the literature and propose a novel paired neural network model. The tourist arrival data is decomposed by two low-pass filters into long-term trend and short-term seasonal components, which are then modelled by a pair of autoregressive neural network models as a parallel structure. The proposed model is evaluated by the tourist arrival data to United States from twelve source markets. The empirical studies show that our proposed paired neural network model outperforming the selected benchmark model across all error measures and over different horizons.

1. Introduction

Tourist flows, regardless the sources and destinations, are all observed seasonally variant. The seasonality is one of the most critical features of the tourism industry and have an important impact on the local tourism economy, which is strongly correlated with the macroeconomic planning, operation and resource allocations in local community. The advantages and disadvantages of the seasonal patterns on local economic development, domestic business, and the macroeconomics have been thoroughly studied in (Butler, 2001) (Lim & McAleer, 2001) and (Chen, Li, Wu, & Shen, 2017). The advantages include the "normal" life style of the local people in low season and the maintenance and recovery of the natural and municipal resources out of the peak season. Nevertheless, the disadvantages include the over-utilization of the resources and infrastructures during peak seasons due to the overwhelming tourist demand and consumption, which may challenge the management of the investment and labour employment for the local government (Butler, 2001) (Chen, Li, Wu, & Shen, 2017). Consequently, tourist arrivals from different source markets, and the arrival forecasting, plays a crucial role in tourism industry, and in the local economy as well. Accurately forecasting tourist arrivals (demands) from every single source is of huge important to the researchers, industry practitioners, and decision-makers.

In the past decades, a big number of forecasting models have been proposed, applied and tested in the tourism forecasting area. (Chen, Li, Wu, & Shen, 2017) thoroughly reviewed and summarized the models proposed in the last two decades in three primary categories: deterministic seasonality, stochastic seasonality and multivariate time series model. The deterministic seasonality model assumes a seasonal unconditional mean that varies with the seasons of the year. Extensive studies investigate the method that extracts the seasonal component from the demand series to generate a seasonally adjusted series, i.e., moving average has been proposed to separate the seasonal component by (Lim & McAleer, 2001) but it is not suitable for forecasting. Stochastic seasonality models, which, on the other hand, dominate the area of tourist demand forecasting in recent literatures, include two types: stochastic stationary and non-stationary seasonality, which assume an invariant (Osborn, Harevi, & Birchenhall, 1999) (Kim, 1999) (Ghysels & Osborn, 2001) and variant seasonal pattern (Lim & McAleer, 2001) (Song, Li, Witt, & Athanasopoulos, 2011) respectively. The latter type, stochastic non-stationary model, has been widely used in recent years and includes two major models: the seasonal autoregressive integrated moving average (SARIMA) family of seasonal unit root models (Alleyne, 2006) (Kulendran & Wong, 2005) (Oh & Morzuch, 2005) and the paired time series model (STSM) (Harvey & Todd, 1983). Both models assume that the tourist arrival data is composed of trend and seasonal components as well as irregular terms. The SARIMA model stabilizes the time series by seasonal and non-seasonal differencing, which is widely applied in financial area for reducing the non-stationarity, while the STSM model implicitly decomposes the time series into stochastic trend, seasonal and irregular terms. Though the SARIMA model is almost the most widely applied model in tourism demand forecasting, the STSM model has been reported to outperform most competing models consistently, including naïve Bayesian, neural network and exponential smoothing models (Kon & Turner, 2005). In addition, STSM model has been proved to outperform the SARIMA model in (Kulendran & Witt, 2003) (Song, Li, Witt, & Athanasopoulos, 2011).

Computational techniques such as machine learning methods, although not studied thoroughly, have also been used in tourism forecasting in a few literatures, among which a few studies confirmed the superior performance of ANN. (Muysal & Roubi, 1999) initially investigated the possibility of applying artificial neural network (ANN) on forecasting the quarterly Canadian tourism expenditures in United States. By selecting the variables that are relevant to the expenditures as well as the lagged expenditure values as the input of the ANN, this study demonstrated the usefulness of a standard structure ANN in tourism demand forecasting. (Law & Au, 1999) applied neural network with six input neurons with six input variables that are relevant to the service, hotel, foreign exchange rate, and market expenses to forecast the annual Japanese tourist arrivals in Hong Kong. It further confirmed the superior performance to regression, naïve, moving average and exponential smoothing. (Law R. , 2000) further applied and highlighted the importance of incorporating the back-propagation method to train the ANN model in forecasting tourist arrivals. (Kon & Turner, 2005) further compared the forecasting performance of ANN with basic paired method (BSM), naïve, and Holt-Winter methods by using the Singapore quarterly tourist arrivals from five source markets. They showed that ANN can achieve the best performance by the standard structure. (Burger, Dohnal, Kathrada, & Law, 2001) applied ANN on monthly tourist arrivals from USA to Durban, South Africa with comparison to widely used competing models and demonstrated that ANN is better to handle non-linear time series than other models.

On the other hand, some other studies showed the traditional models outperforming the ANN. (Claveria & Torra, 2014) further analysed the performance of ANN in forecasting tourism demand of Catalonia from more than ten source markets. They found that the ARIMA model performed the best in most cases especially in short horizon forecasting while the ANN was the most underperformed model. It is noted that this study used a structure of ANN with one lag input and three hidden neurons, which is usually considered as an over-simple structure and often results in an underfitting problem. This paper also claimed that the structure of ANN might be further improved for a better performance. (Hassani, Silva, Antonakakis, Filis, & Gupta, 2017) thoroughly evaluated the forecasting performance across seven popular models by the monthly international tourist arrival data in nine European countries across Jan 2000 to Dec 2013. The Singular spectrum analysis (SSA), ARIMA and Trigonometric box-cox ARMA trend seasonal model (TBATS) have been evaluated as the best-performed models while other models including neural network provided the least accurate results. It is noted that the ANN model used in this study contained 2-lagged input and 1 hidden neuron, which is, again, an over-simple structure and is usually underfitting the data. (Pai, Hung, & Lin, 2014) proposed a new logarithm least-squares support vector regression (LLS-SVR) model and applied in forecasting the tourist arrivals to Taiwan and Hong Kong. LLS-SVR is a revised model based on the well-known computational method: support vector machine (SVM) and it achieved superior performance to those of the traditional methods. It also claimed that ARIMA model is slightly underperformed in capturing the trend of the data and is therefore not suggested for forecasting the tourist arrival data (Pai, Hung, & Lin, 2014).

As the studies in (Claveria & Torra, 2014) and (Hassani, Silva, Antonakakis, Filis, & Gupta, 2017), the ANN has been applied in tourist arrival data forecasting for the last two decades, it, however, has been treated merely as a black-box with the simplest structure with 1 to 2 lags input and 1 hidden neuron. It is noted that an ANN with a single hidden neuron equipped with sigmoid activation function is functionally equivalent to a logistic regression with bias term, which apparently may not be able to capture the strong non-linearity and seasonality in the tourism data. In addition, previous studies usually directly fed the original tourism data into the ANN model and expected a "magic" forecasted output. Almost no study has thoroughly revised and tailor-made the ANN for a specific application in tourism area with respect to the significantly different patterns in this area.

In this paper, we address this problem by proposing a novel method that makes use of the capability of the computational methods. ANN is strong in capturing the non-linearity of the time series especially the detrend series (Zhang & Qi, 2005), while autoregressive neural network, may not be strong in modelling the strong seasonal patterns (Zhang & Qi, 2005) (Patil, Tantau, & Salokhe, 2008).

Inspired by the work in (Yao, et al., 2017), we propose a methodology specifically for modelling tourism data. We assume the existence of an increasing trend plus a repeated annual seasonality with slightly different amplitudes in the tourism data following the work in (Chen, Li, Wu, & Shen, 2017). We firstly extract the trend and seasonal components explicitly by the mathematical tools in (Harris, Stoja, & Yilmaz, 2011) (Yao, et al., 2017) subject to certain constraints of the seasonal components. We use the autoregressive neural network (ARNN) to model the extracted trend and seasonal components separately following (Yao, et al., 2017). The contribution of this paper is in two strands. The first is to answer a question: can ANN-based model achieve better performance than traditional models in forecasting tourists. Different from the work in (Claveria & Torra, 2014) and (Hassani, Silva, Antonakakis, Filis, & Gupta, 2017), this study proposes an application-specific approach of a pair of autoregressive neural network (ARNN) to model and forecast the tourists. The decomposition tools, stationarity test and two separated ARNNs in the approach provide a statistical-principled manner instead of the heuristics to decompose and model the tourism data. On the other hand, the approach satisfies the assumption of stationary seasonality in tourism studies. This approach, as far as we aware, is the first tailor-made NN based model according to the intrinsic feature of the tourism data. The evaluations in Section 3 show a consistently better forecasting performance of the proposed approach. The second is a thorough performance study of the proposed approach with a few decomposition methods under heuristic parameter selection, although our approach determines the parameters based on a statistical principle. Explicit decomposed components rely on certain parameters of different tools. Selecting appropriate parameter determines the forecasting performance of the whole model. This is as far as we aware, the first comparison study of the well-known decomposition methods and the corresponding forecasting performances.

The rest of this paper is structured as follows. In Section 2, our proposed model is discussed in detail. In Section 3, the data and the empirical studies are also introduction as well as the analysis of the performance of the out-of-sample forecasting results. The Section 4 concludes.

2. Model and Research Method

We propose a simple and effective method to construct a pair of Neural Network (*p*NN) for the tourist arrival forecasting. We represent the tourist arrival data as the variable y_t, and construct *p*NN following the form of the basic paired model defined in (Harvey & Todd, 1983) as

$$y_t = \mu_t + \gamma_t, \tag{1}$$

where t=1, ..., T, μ_t and γ_t are trend and seasonal components respectively. We assume the seasonal component γ_t following a stationary autoregressive process of order s: $AR(s)$, where s is the number of "seasons" in a year (Harvey & Todd, 1983). To maintain such assumption, we do not follow the originally defined form of trend in (Harvey & Todd, 1983); instead, we assume that μ_t follows a smooth and non-stationary process but leave its precise dynamics unspecified.

The *p*NN is a methodological framework containing three steps:

- Step 1: extracting the trend component μ_t from y_t explicitly subject to the stationarity of the seasonal component γ_t;
- Step 2: modelling the trend and seasonal component, μ_t and γ_t, by two autoregressive neural networks separately;
- Step 3: generating the *n*-step ahead forecasting results, $\hat{\mu}_{t+n}$ and $\hat{\gamma}_{t+n}$, separately and aggregating them as the final forecasting results as $\hat{y}_{t+n} = \hat{\mu}_{t+n} + \hat{\gamma}_{t+n}$.

We introduce the implementation of *p*NN with different techniques and compare their performances.

2.1 Step 1: trend and seasonality decomposition

We implement the explicit extraction of the trend component μ_t from y_t by three well-known methods: 1) the low-pass Hodrick-Prescott (HP) filter (Hodrick & Prescott, 1997); 2) the wavelet transformation (WT) method (Daubechies, 1992); and 3) a simple moving average (MA) method (Lim & McAleer, 2001). We tune the parameters of those methods to obtain the μ_t subject to the stationarity of the seasonal component γ_t, obtained by $\gamma_t = y_t - \mu_t$. The stationarity of γ_t is tested and determined through a statistically principled manner: the Augmented Dickey-Fuller (ADF) test (Fuller, 1976), which has the null hypothesis that a unit root is present in the seasonal component. Thus, the extraction of the trend μ_t is a process that optimizes the appropriate parameters of the decomposition methods (i.e., HP, WT, and MA) to satisfy the stationarity constraint of the seasonality γ_t.

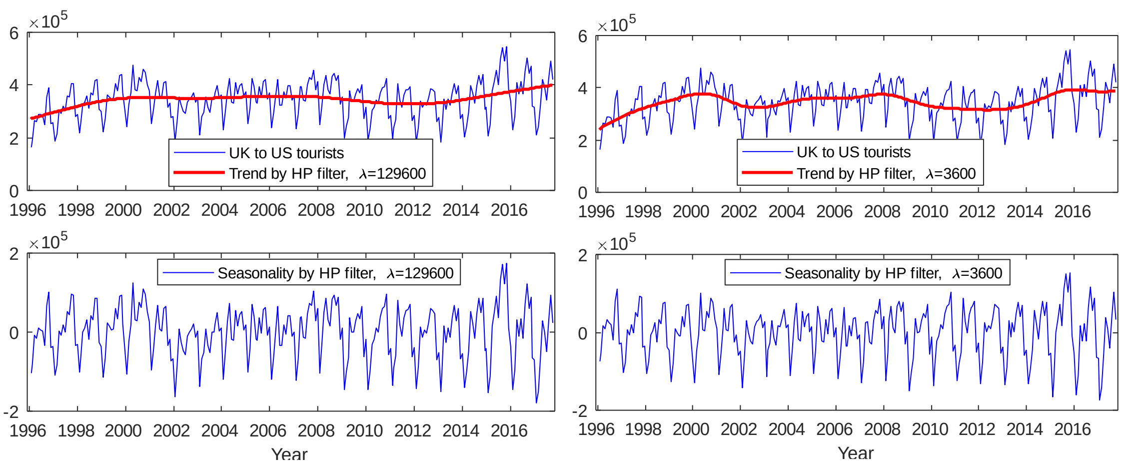
The explicit extraction of the trend component is due to three reasons. The first is to satisfy the assumption of a stationary and autoregressive seasonal component, which otherwise was not guaranteed but merely assumed in traditional paired model (Harvey & Todd, 1983) and seasonal ARIMA model (Kulendran & Wong, 2005). The second is to statistically and deterministically generate the trend and the seasonal components, which were otherwise not explicitly defined and uneasily to observe (Harvey & Todd, 1983) (Kulendran & Wong, 2005). Therefore, the explicit extraction provides an interpretable method that generate the economic meaningful and easily illustrated forecasting results. The third is that we hypothesize that separately modelling two components may achieve better forecasting performance than the traditional models.

Low-pass Hodrick-Prescott (HP) filter

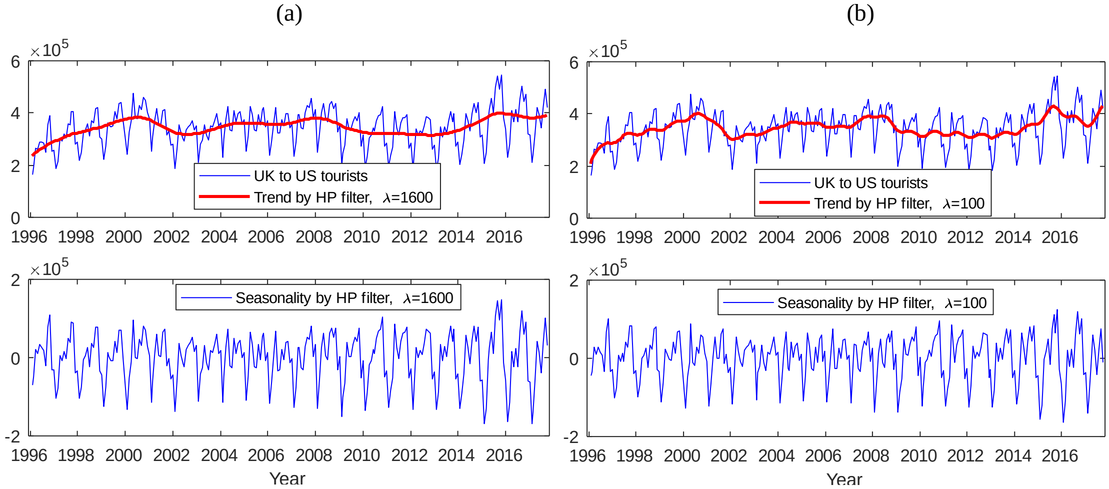
The HP filter was proposed in (Hodrick & Prescott, 1997) and is widely applied in macroeconomics for removing the short-run cyclical component and revealing the low-frequency non-linear trend of a time series (Stock & Watson, 1999) (McElroy, 2008) (Stock & Watson, 2016). For a time series data y_t, given the value of the smoothing parameter λ, the trend component μ_t can be obtained by solving the following:

$$\min_{\mu_t}\left(\sum_{t=1}^{T}(y_t - \mu_t)^2 + \lambda \sum_{t=2}^{T-1}[(\mu_{t+1} - \mu_t) - (\mu_t - \mu_{t-1})]^2\right) \tag{2}$$

where the smoothing parameter λ penalizes the variation in the growth rate of the trend component μ_t. The larger the λ, the heavier the penalty for variation, and the smoother the μ_t. Therefore, the implementation of Step 1 by HP filter is to select an appropriate value of λ to maintain the stationarity of γ_t. The λ value selection is usually started from $\lambda = 129600$, the empirical value recommended in (Baxter & King, 1999) and (Ravn & Uhlig, 2002), down to $\lambda = 0$. For each value of λ, we apply ADF testing on the γ_t, once the null is rejected, which suggests the seasonal component is stationary, the stationarity condition is then satisfied. We show in Figure 1 an example of selecting the value of λ by the HP filter. The data is monthly tourist arrivals of US from UK in the period Jan 1996 to Sep 2017. We start with $\lambda = 129600$ in Figure 1(a) and apply ADF test at each value of λ until the case in Figure 1(d), where the selection procedure yields a $\lambda = 100$ with a highly significant *p*-value at 0.001 for ADF test. Figure 1(b) and (c) are two examples of the intermediate λ values 3600 and 1600 of the selection process. We observe a pattern that as the smoothing parameter decreases, the trend component becomes less smooth and the resulting seasonality component slowly turns more into a stationary seasonal process in Figure 1(d), which fulfils the assumption of basic paired time series model proposed in (Harvey & Todd, 1983).



(a) (b)

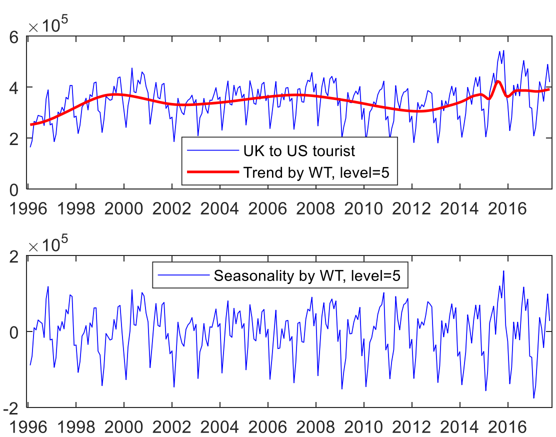


(c) (d)

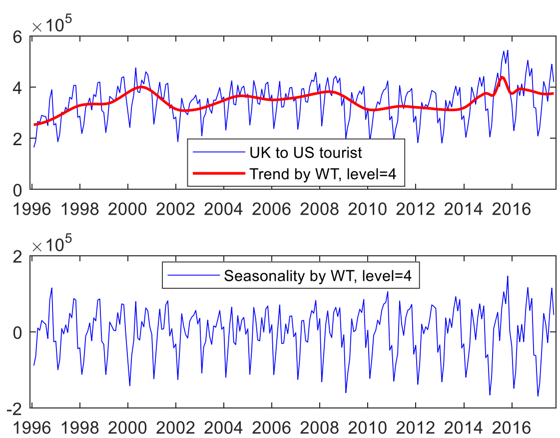
Figure 1 This figure shows the trend and seasonality decomposition by HP filter with different values of parameter $\boldsymbol{\lambda}$. In upper parts of (a)-(d), blue curves represent the monthly tourist arrival from UK to US from Jan 1996 to Sep 2017 and the red curves are the trend component by HP filter with $\boldsymbol{\lambda}$ value of 129600, 3600, 1600 and 100 respectively. In the lower parts of (a)-(d), blue curves are the corresponding seasonal component obtain as the difference between the arrival data and the trend component respectively.

Wavelet transformation (WT) method

Wavelet analysis has been successfully applied to de-noise the option prices to obtain accurate option-implied risk neutral density (Haven, Liu, & Shen, 2012) and was also successfully used in volatility forecast (Barunik, Krehlik, & Vacha, 2016) and high frequency financial data mining (Sun & Meinl, 2012). A key feature of the wavelet transform is that it can decompose any square integrable function into a combination of some scaling function and wavelet functions, each factored by their corresponding approximation coefficients and detail coefficients. Once the original function has been decomposed at certain level, its detail coefficients can be manipulated for de-noise purpose via a "hard" or "soft" thresholding (see (Daubechies, 1992) for a more general background of wavelet transform and de-noise application). Following (Haven, Liu, & Shen, 2012), the choice of the highest decomposition level is the empirical value 7 and the lowest value is 1. We show examples of trend and seasonal components decomposed by WT with level of 5, 4, 3 and 2 during the level selection process in Figure 2 using monthly data of tourist arrival from UK to US from Jan 1996 to Sep 2017, the same data as Figure 1. We can also clearly observe that as the level decrease, the trend component is more non-linear and leaves the seasonal component more stationary. The ADF test stops at WT with level of 3 and shows a stationary and autoregressive seasonal component in Figure 2(c).



(a)



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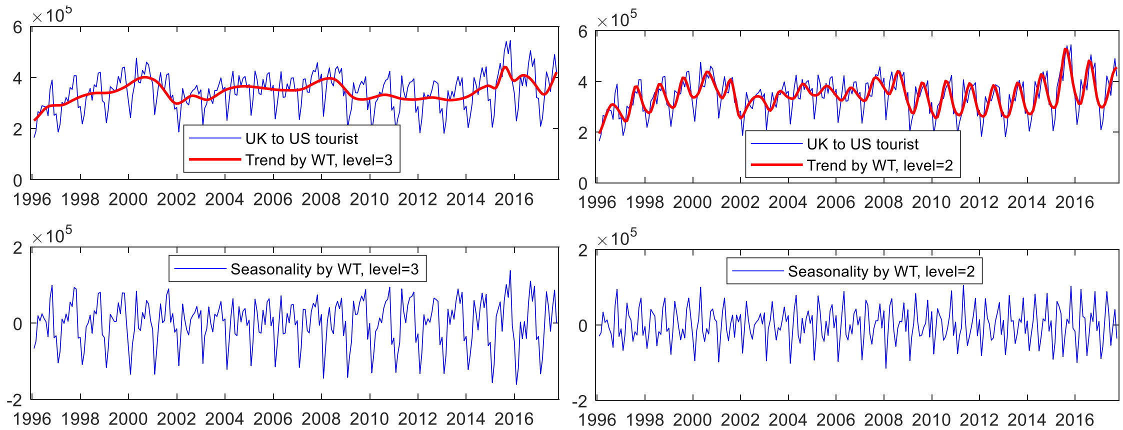


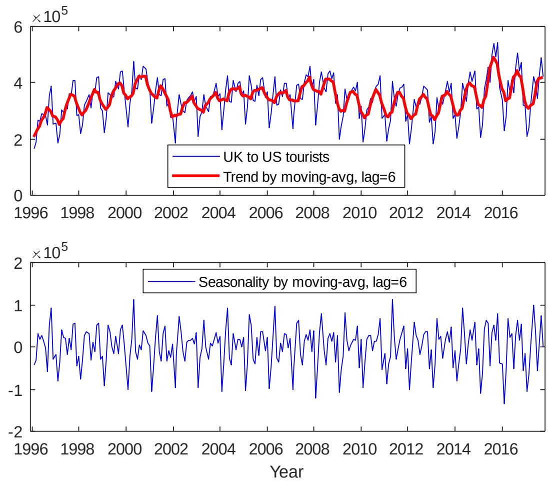
(c) (d)

Figure 2 This figure shows the trend and seasonality decomposition by Wavelet Transformation (WT) with different levels. In upper parts of (a)-(d), blue curves represent the monthly tourist arrival from UK to US from Jan 1996 to Sep 2017 and the red curves are the trend component by WT with level 5, 4, 3 and 2 respectively. In the lower parts of (a)-(d), blue curves are the corresponding seasonal component obtain as the difference between the arrival data and the trend component respectively.

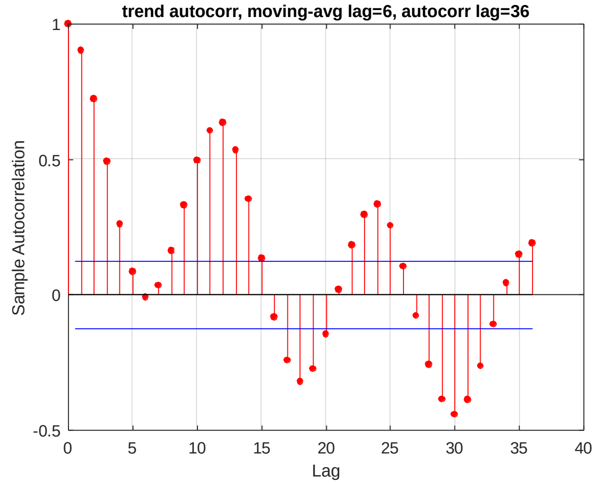
Simple Moving Average (MA) method

Simple moving average (MA) is usually used as a technical indicator in financial market. MA is considered as the equilibrium level of the equity price, which may oscillate apart or toward to the equilibrium level. In 2001, Lim et al applied MA as a method to separate the seasonal component from the tourist arrival (Lim & McAleer, 2001) although MA may not be effective in tourism area due to the correlation between the trend and the seasonal components. Following the study of (Lim & McAleer, 2001), we apply MA as one of the decomposition methods comparable with the HP and WT. Determining the number of lag of the MA is to obtain a seasonal component and a non-seasonal trend component. Therefore, we check the autocorrelation of the trend component and heuristically select the lag of the MA.

Since the original data y_t shows a highly annual cyclical pattern, a lag value of $12n$, n=1, 2… can effectively remove the cyclicality. We show an example in Figure 3 with the same data as in Figure 1. The lag value is heuristically selected as 6, 9 and 12, thus the corresponding trend components are shown in Figure 3(a), (c) and (e) respectively, and the autocorrelations of the trends are shown in Figure 3(b), (d) and (f) respectively. We can clearly observe that the repeat pattern of the trend correlations is decreasing from lag value 6 to 12 and is non-seasonal at lag of 12. Therefore we accept the moving average with lag value 12 as the trend component in Figure 3(e).



(a)



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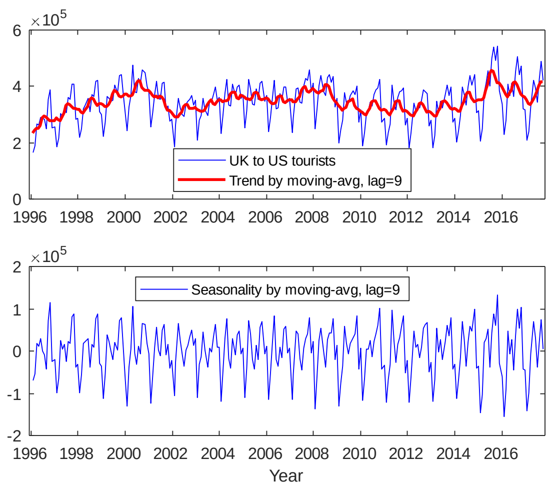

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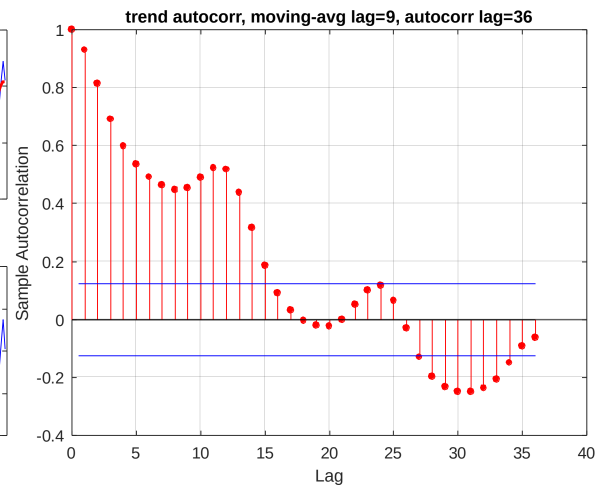

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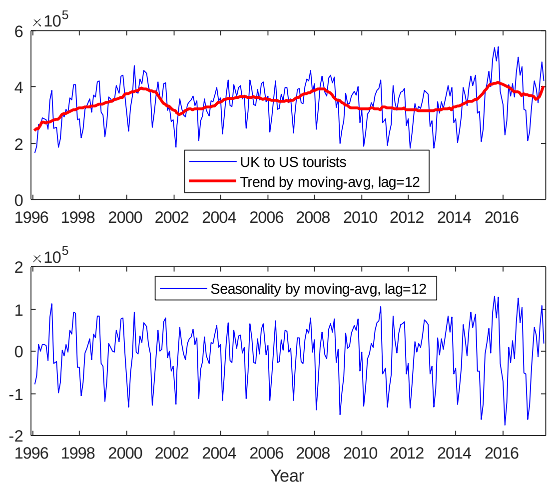
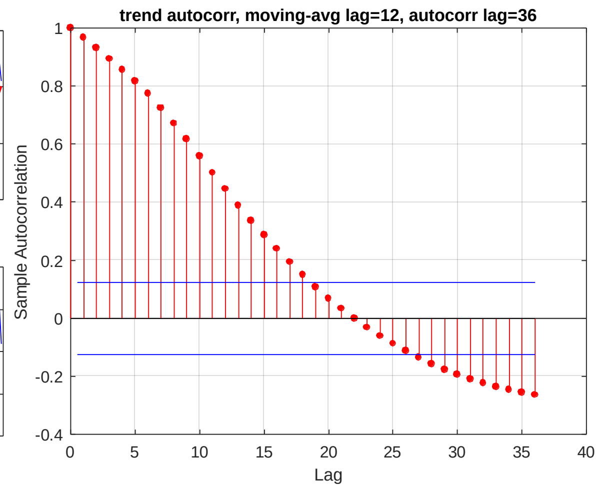


(e)



(f)

Figure 3 This figure shows a comparison of the seasonality of the trend component extracted by the moving average method with lag values 6 and 12. In upper parts of (a,c,e), blue curves represent the monthly tourist arrival from UK to US from Jan 1996 to Sep 2017 and the red curves are the trend component by moving-average (MA) with lag of 6, 9, and 12 respectively. In the lower parts of (a,c,e), blue curves are the corresponding seasonal component obtain as the difference between the arrival data and the trend component respectively. The figures (b,d,f) show the auto-correlation of the trend components in (a,c,e) respectively.

We also show the autocorrelation of the seasonal component in Figure 3(e) in Figure 4. The seasonal component is extracted by MA with lag of 12. The figure clearly shows a cyclical pattern in the seasonal component: the correlation repeats significantly at lag=12*n*, where *n*=0,1, … It means an annual repeated tourist arrival phenomenon.

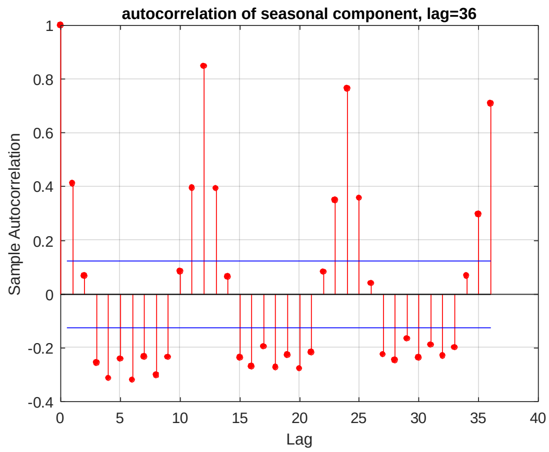


Figure 4 This figure shows the autocorrelation pattern of the seasonal component of the US tourist arrival from UK data in Jan 1996 to Sep 2017. The seasonal component is extracted by MA with lag of 12. The figure clearly shows a cyclical pattern in the seasonal component: the correlation repeats significantly at lag=12*n*, where *n*=0,1, … It. It means an annual repeated tourist arrival phenomenon.

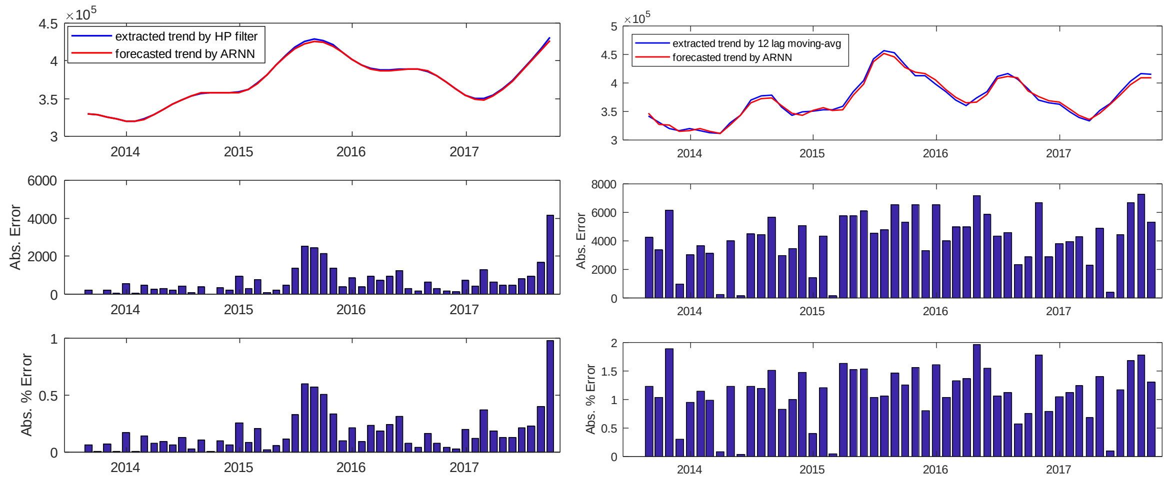
2.2 Step 2: modelling the trend component

After decomposing the trend and the seasonal component, an AutoRegressive Neural Network (ARNN) is applied to the trend component μ_t. The ARNN is widely used in time series modelling and proved to outperform traditional models, i.e., the GARCH, EGARCH, and ARFIMA in deseasonalized financial area (Zhang & Qi, 2005) (Patil, Tantau, & Salokhe, 2008) (Kristjanpoller, Fadic, & Minutolo, 2014) (Kristjanpoller & Minutolo, 2016) and also performs better than recurrent feed-forward neural network with less sensitivity to the problem of long-term dependence (Mustafaraj, Lowry, & Chen, 2011). In this study, to model the trend component μ_t, we use ARNN with three layers, which include an input layer with lagged μ_t inputs to the network, a hidden layer with hyperbolic tangential activation function and an output layer with a linear regression function. The general form of ARNN for one-step ahead forecasts is as in (Siegelmann, Horne, & Giles, 1997) and (Mustafaraj, Lowry, & Chen, 2011):

$$\hat{L}_t(\theta_{\text{ARNN}}) = g[\varphi_i(t), \theta_{\text{ARNN}}] = F_j \sum_{u=1}^{N_h} W_{j,u} f_u\left(\sum_{i=1}^{N_u} \varphi_i(t) w_{u,i} + w_u\right) + W_j \quad (3)$$

where $g[\varphi_i(t), \theta_{\text{ARNN}}]$ is the ARNN function; N_h is the number of hidden neurons and N_u is the number of input variables; $W_{j,u}$ is the weights vector from the hidden neurons to the output layers; $w_{u,i}$ represents the matrix that contains the weights from the external input N_u to the hidden neurons N_h; w_u and W_j are the biases of hidden and output layers; $\varphi_i(t)$ is the vector that contains the regression parameters of the AR part of the neural network; and θ_{ARNN} specifies the parameters vector, which contains all the adjustable parameters of the neural network. In this paper, to model the trend component, we start with the widely used configuration for the ARNN following the (Siegelmann, Horne, & Giles, 1997) and (Mustafaraj, Lowry, & Chen, 2011): N_u=4, and N_h=10, which means a 4-lag input and a 10-neuron hdden layer. Therefore, the forecasting is based on current value of the μ_t as well as the previous 3 lags, μ_{t-1}, μ_{t-2}, and μ_{t-3}. To find the best configuration, we also test the performance with N_h=5, 10, 15 and 20 and N_u=4, 6 and 8.

This is a supervised-learning neural network, where the model parameters are "trained" to map the input-output variables via the modified Levenberg-Marquardt (Hagan & Menhaj., 1994) algorithm, which is to minimize the quadratic error by descent of the maximum gradient. The following Figure 5 shows two examples of forecasting the trend component by trained ARNN using the same data as Figure 1. In Figure 5(a), the trend component is extracted by HP filter with $\lambda = 100$ and in Figure 5(b), the trend component is obtained by 12 lag moving average. The trend component data from Jan 1996 to Jul 2013 in (a) and (b) are used to train the ARNN model separately and the remained data from Aug 2013 to Sep 2017 is used for out-of-sample testing the two ARNN models. In the upper part of Figure 5(a), the forecasted (red) and the extracted trend components are illustrated and show a very closed pattern. The middle and lower parts of Figure 5(a) and (b) show the absolute error and absolute percentage error of the two forecasted trends respectively. We observe very competitive performances of below 1% error in (a) and below 2% error in (b) by ARNN, although the error in Figure 5(b) is higher than (a) due to the non-smoothness of the trend by moving average.



(a) (b)

Figure 5 This figure shows an example of forecasting the trend component only by ARNN model. (a) in the upper figure, the blue curve is the trend component extracted from the monthly tourist arrival from UK to US from Aug 2013 to Sep 2017 via the HP filter with $\boldsymbol{\lambda = 100}$. The red curve is the forecasted trend by ARNN, which is trained by the trend component data from Jan 1996 to Jul 2013. The middle and lower figures show the absolute error and absolute percentage error of the forecasted trend respectively; (b) in the upper figure, the blue curve is the trend component by the 12 lag moving average of the same data. The red curve the forecasted trend by ARNN. The middle and lower figures show the absolute error and absolute percentage error of the forecasted trend respectively.

After modelling the trend component, we model the seasonal component by a separated ARNN model. (Song, Smeral, G. Li, & Chen, 2013) found that a four-quarter lag time-varying parameter model can capture seasonal patterns well in forecasting the quarterly tourist arrival series. Inspired by this study, we simply extend the lag to 12-month to forecast the monthly tourist arrival series in our *p*NN models. This also complies with the autocorrelation test in Figure 4, where the seasonal component shows a clear annual cycle at lag=12*n*, where *n*=0,1…. Therefore, setting the number of the seasons in a year s as 12 reflects the nature of the data and complies with the literature.

2.3 Step 3: *n*-step ahead forecasting

Finally, the *n*-step ahead forecast of the monthly tourist arrivals is the sum of the output from two separated ARNN models according to the deterministic equation (1): $\hat{y}_{t+n} = \hat{\mu}_{t+n} + \hat{\gamma}_{t+n}$, where $\hat{\mu}_{t+n}$ and $\hat{\gamma}_{t+n}$ are the *n*-step trend and seasonal component forecasting results generated by two separated ARNN models respectively.

2.4 Flow of the methodology

We illustrate the implementation of a pair of Neural Network (*p*NN) in the following Figure 6. In this figure, the key steps of implementing the *p*NN, the decomposition of the trend component, testing of the stationarity of the seasonal component and the two separated autoregressive neural networks are shown with the data flow diagram.

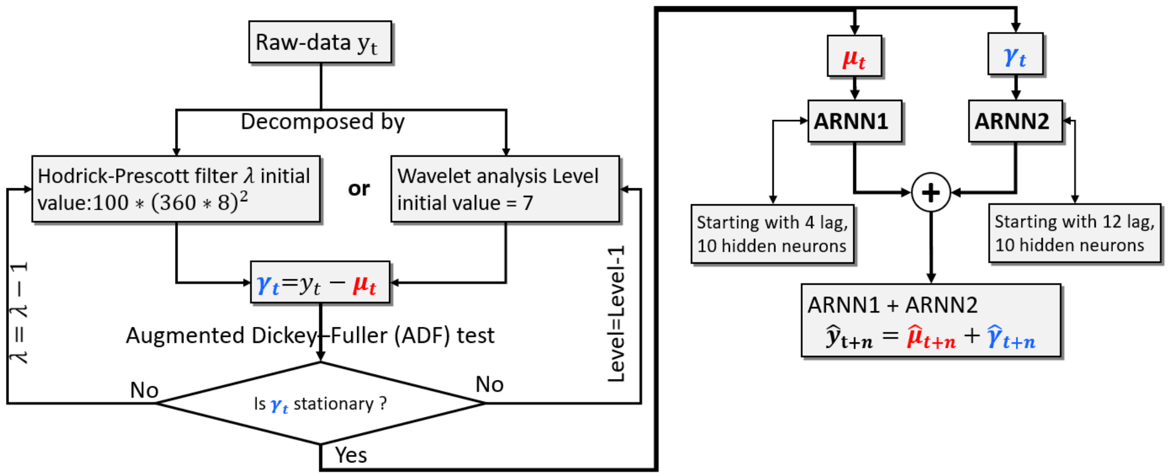
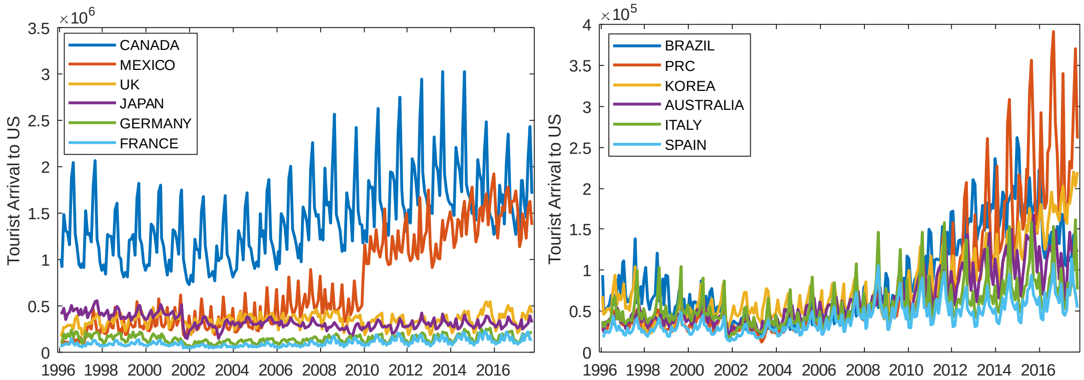


Figure 6 This figure shows the implementation flow of the pair of autoregressive neural network (*p*NN) method

3. Forecasting evaluation

3.1 Data and *p*NN configurations

The empirical study of the propose *p*NN is based on US monthly inbound tourist arrivals from top 12 source markets, including Mexico, Canada, China Mainland, Japan, United Kingdom, South Korea, Brazil, Germany, Australia, France Italy and Spain in the last 22 years (from Jan 1996 to Sep 2017). The time series data for each source market are downloaded from the official website of *National Travel & Tourism Office*. The Figure 7 shows an illustration of the inbound tourist arrival data series of the top 12 source markets from Jan 1996 to Sep 2017. It is obviously that over the last six years from 2010 to 2016, tourist arrivals from Mexico and China Mainland have a jump increase. Note that the significantly seasonal pattern is a normal feature of US inbound tourist arrival across all source market.



(a) (b)

Figure 7 This figure shows all tourist arrival data to US from Jan 1996 to Sep 2017; (a) the tourist arrival from top 6 source markets: Canada, Mexico, UK, Japan, Germany, France; (b) the tourist arrival from the 7th-12th source markets: Brazil, China Mainland, South Korea, Australia, Italy, and Spain.

To obtain the best forecasting result, we compare the performances of the whole *p*NN under different configurations of the two ARNN models. We summarize the configurations in Table 1.

Table 1 This table summarizes the configurations of a pair of ARNN models for trend and seasonal components respectively.

	Input lag N_u	Hidden neuron N_h	Training length
ARNN trend	4, 8, 12	5, 10, 15, 20	From 2 years to 19.5 years with step of 0.25 year
ARNN seasonal	12		

Therefore the *p*NN performance evaluation is composed of two parts:

1) Part 1-Performance study under different configurations: we construct *p*NN model under the configurations in Table 1 and compare the performances to obtain an appropriate configuration for *p*NN;
2) Part 2-Performance comparison: we construct *p*NN with HP, WT, and MA under the selected configuration and compare the performance with the benchmark models.

3.2 Benchmark Models

The *p*NN models are constructed by three steps in Section 2 with the low-pass Hodrick-Prescott (HP) filter, wavelet transformation (WT), and the moving-average (MA) and are named as *p*NN-HP, *p*NN-WT, and *p*NN-MA. As the comparison, selected traditional econometrics models are also included as the benchmark. The Seasonal Autoregressive Integrated Moving Average (SARIMA) model assumes that the tourist arrival data is also composed of trend and seasonal components as well as irregular terms. It stabilizes the time series by seasonal and non-seasonal differencing, which is widely applied in financial area for reducing the non-stationarity. As the SARIMA model is almost the most widely applied model in tourism demand forecasting, and performs reasonably well (Alleyne, 2006) (Kulendran & Wong, 2005) (Oh & Morzuch, 2005), it is selected as one of the benchmark models with other two traditional models, autoregressive integrated moving average (ARIMA) and autoregressive fractionally integrated moving average (ARFIMA) model.

For the first part of the evaluation, we select the *p*NN-HP, *p*NN-WT, and *p*NN-MA as the example to test the performances of the model using different length of training data. The training dataset is selected from 2 years up to 19.5 years. For each length, the *p*NN-HP, *p*NN-WT, and *p*NN-MA model is trained and then tested at horizon of 1 month to 18 months (1.5 years).

For the second part, we employ a rolling-window mechanism to evaluate the forecasting performance. The data in the rolling-window is used to estimate the models and the remained following-up data is used as the testing dataset. The initial window, *W1*, is set to from Jan 1996 to Mar 2016 and the remained data of 18 months, from Apr 2016 to Sep 2017 are set to the testing dataset. The models are, firstly, estimated by the data in *W1*, and then, tested by the remained data of 18 months for a set of horizon h of 1 to 18 months ahead forecasts. After this, the initial window slides one month forward to *W2*, covering from Feb 1996 to Apr 2016, for estimating the models, and the remained data of 17 months, from May 2016 to Sep 2017 is for testing the models. In this round, a set of horizon h of 1 to 17 months ahead forecasting results are generated and tested. Similarly, the model estimation and forecasting are recursively repeated until all remained data are used up. In the end, the rolling-window forecast mechanism generates 19-h sets of h (h=1, …, 18) months ahead forecasting results, which is, 2052 in total (12 source markets and 171 forecasts in each market).

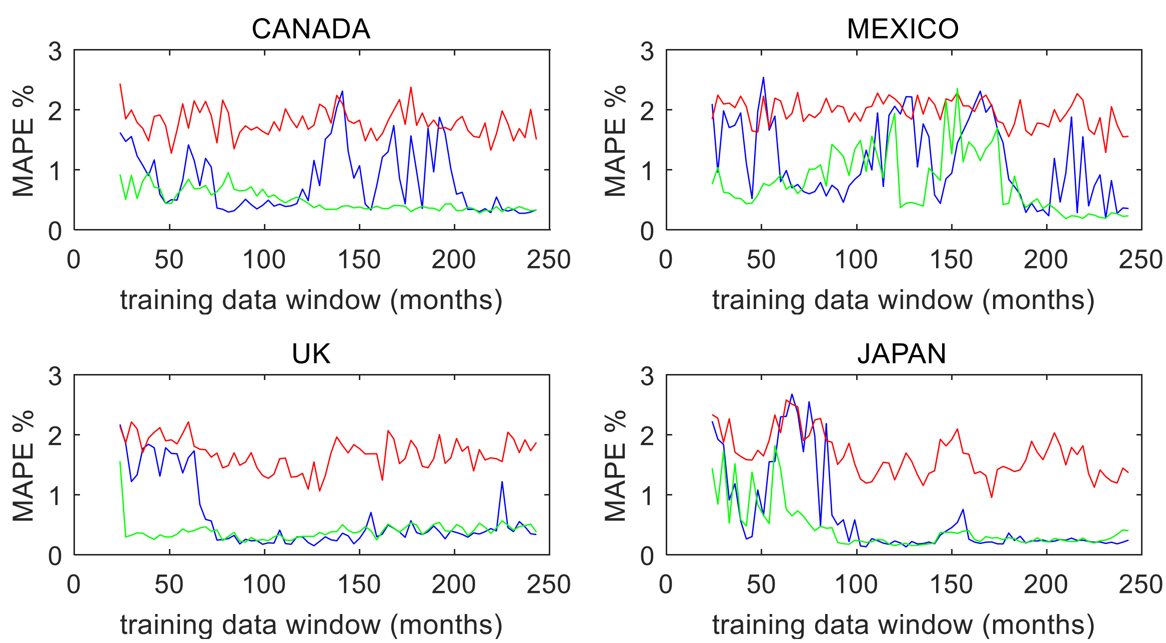
The forecast accuracy is evaluated by the Mean Average Absolute Percentage Error (MAPE) as it is a relative measure and comparable across different datasets. In addition, the forecasted values of the tourist arrivals are also shown as examples for a closer insight.

3.3 Empirical Result

3.3.1 Part 1: Performance study under different configurations

<u>Training length</u>

To find out an optimal length of training dataset for all models, we train *p*NN models with 4 input lags and 10 hidden neurons. Such configuration is merely for the length determination. Thus, we train *p*NN-HP, *p*NN-WT, and *p*NN-MA as well as ARIMA and ARFIMA models by twelve datasets with length from 2 to 20 years. We test the trained models by forecasting the values at 1 to 18 months (1.5 years) horizons. The MAPE performance of the *p*NN-HP, *p*NN-WT, and *p*NN-MA against different length of training dataset are shown in Figure 8(a). As the *p*NN-HP, *p*NN-WT, and *p*NN-MA show relatively better performances at training dataset longer than 200 months (16.7 years), to obtain a generic length of the dataset, we calculate the average MAPE of the three models across twelve datasets in Figure 9. We can clearly observe that training the models by the data of 210 (17.5 years) months achieves the best generic performance. Similarly, the benchmark models, ARIMA and ARFIMA, are estimated and tested as the same method. The average MAPE of ARIMA and ARFIMA across all datasets are shown in Figure 8(b) (The MAPE of ARIMA and ARFIMA on each single dataset is shown in appendix). As we can also clearly observe that with the training dataset of 210 months, those two models achieve the best performance, although the overall performance is around 50% and is significantly lower than the one in Figure 8(a), which is around 2%.



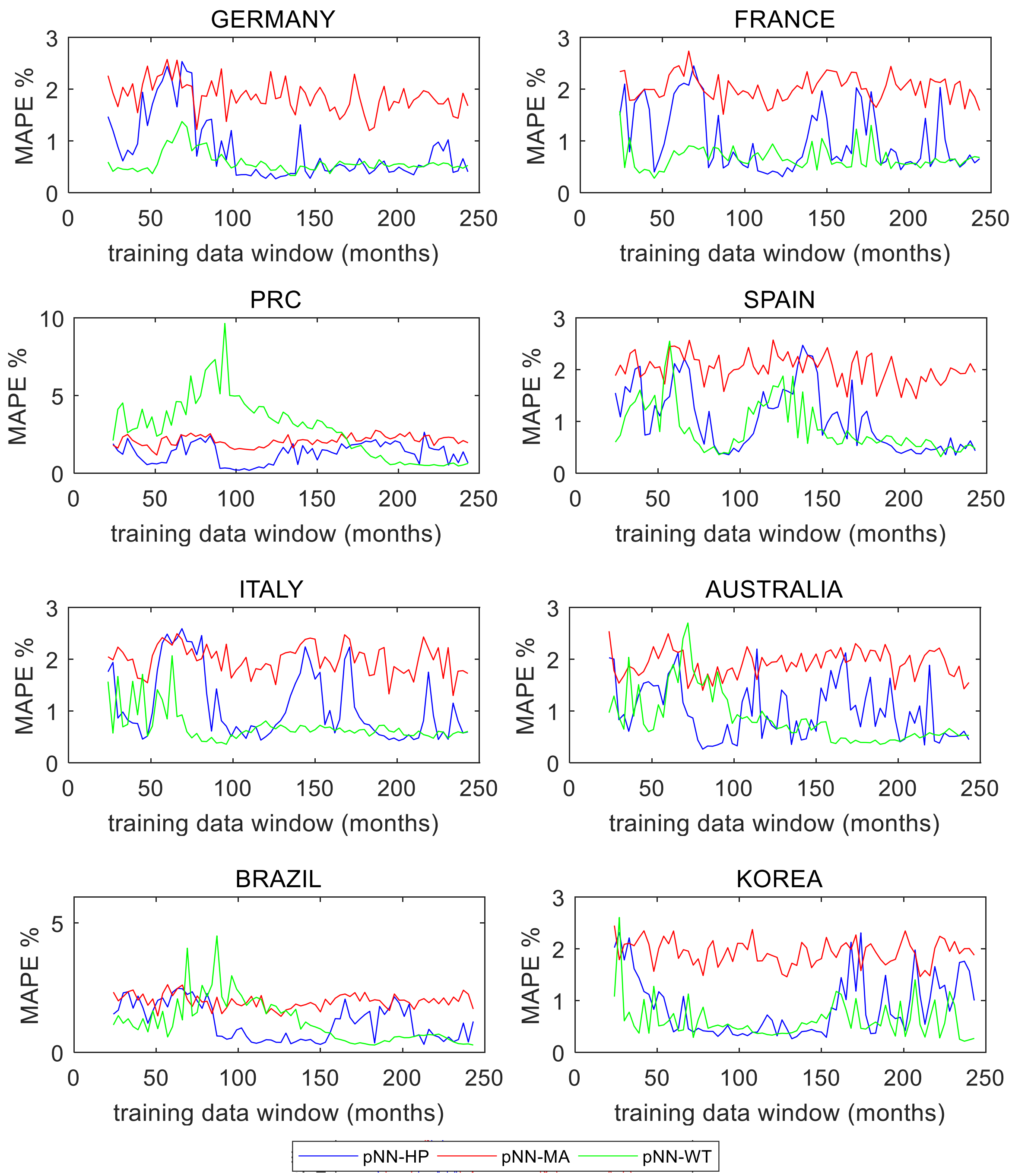
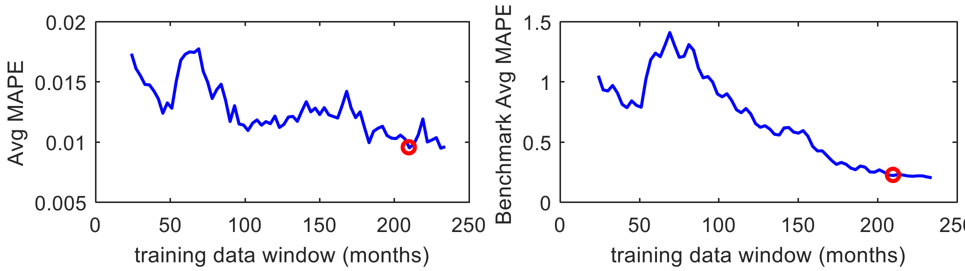


Figure 8 This figure shows the performance (MAPE) of the *p*NN-HP, *p*NN-MA, and *p*NN-WT by the training dataset with length from 2 to 20 years. The evaluation is based on tourist arrival data to US from top 12 source markets: Canada, Mexico, UK, Japan, Germany, France, China, Spain, Italy, Australia, Brazil and Korea in the time period from Jan 1996 to Sep 2017.



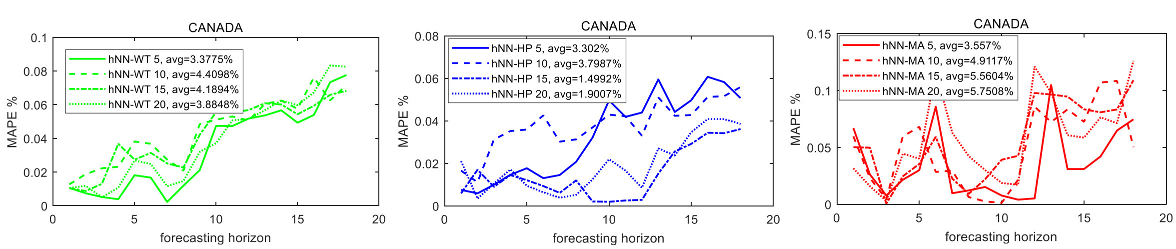
(a) (b)

Figure 9 This figure shows the average MAPE of (a) the *p*NN-HP, *p*NN-MA, and *p*NN-WT; and (b) ARIMA, and ARFIMA across all datasets in Figure 8. The red circle indicates the best generic performance. The length of the training dataset at best-performed point is 210 months, equivalent to 17.5 years.

Tourism industry is not a data-intensive area as the tourist arrival is usually recorded monthly, which means that training a model using the data of 17.5 years and forecasting 1.5 years ahead is merely equivalent to forecasting 18 data samples ahead based on 210 historical data samples. Such a configuration has been proved by the empirical studies on twelve datasets as the best one in terms of the forecasting performance.

Hidden Neurons

After determining the length of the training dataset, we tune the number of hidden neurons in *p*NN models to obtain an optimal parameter. We train the *p*NN-HP, *p*NN-WT, and *p*NN-MA models using the data of 17.5 years with 5, 10, 15 and 20 hidden neurons and show the 1 to 18 months (1.5 years) forecasting performance by MAPE. We show the MAPE performance of *p*NN-HP, *p*NN-WT, and *p*NN-MA models on four examples, tourist arrival from Canada, Mexico, UK and Japan. The average MAPE across all forecasting horizons are shown in the Figure 10. To illustrate an overall performance , we calculate the average MAPE of *p*NN-HP, *p*NN-WT, and *p*NN-MA models across all horizons and show then in the Table 2. It is quite clear that in all datasets except Korea, the *h*NN model with 5 hidden neurons achieves the lowest average MAPE. We therefore follow the empirical study and train the *h*NN models with five hidden neurons.



(a) (b) (c)

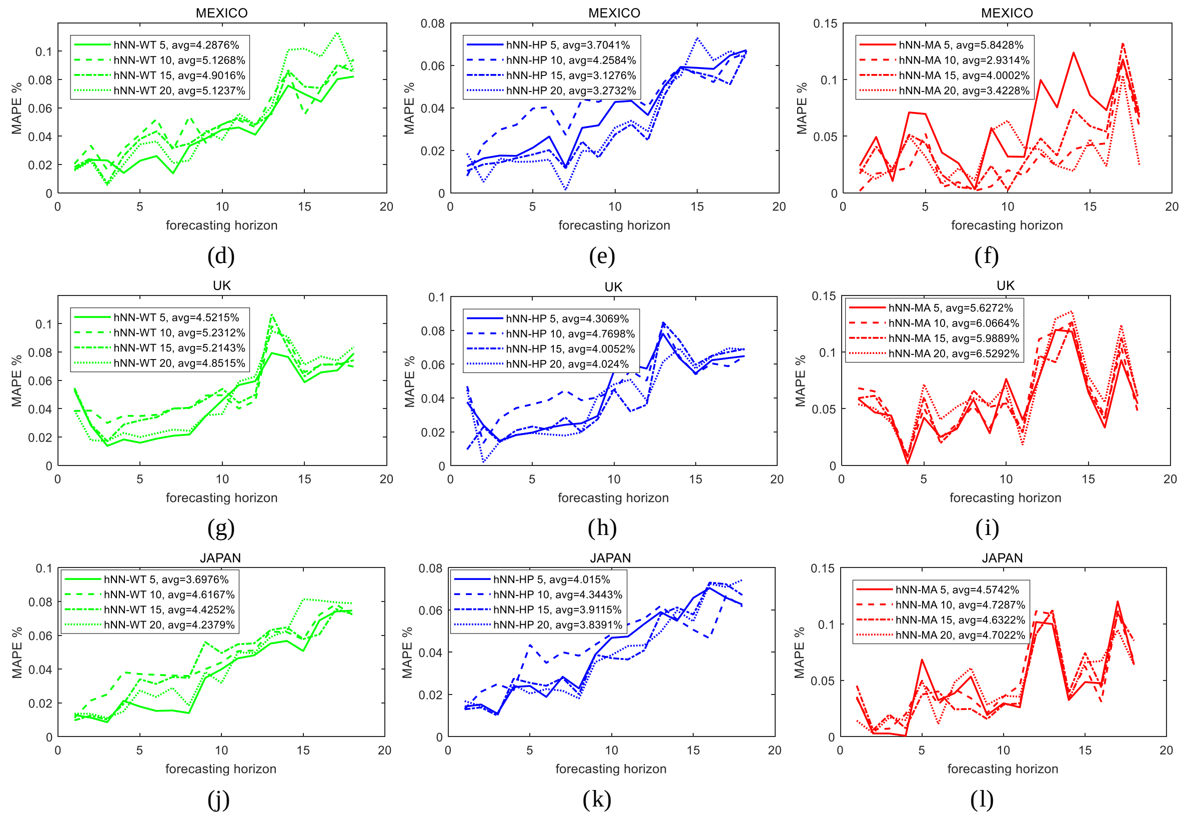


Figure 10 This figure shows four example datasets of the testing MAPE of *p*NN-HP, *p*NN-WT, and *p*NN-MA models trained with 5, 10, 15, and 20 neurons.

Table 2 This table shows the average MAPE of three models, *p*NN-HP, *p*NN-WT, and *p*NN-MA, over all forecasting horizons under the configuration of 5, 10, 15, and 20 hidden neurons.

hidden neuron	MEXICO	CANADA	PRC	JAPAN	UK	**KOREA**
5	**3.9399%**	**3.4122%**	**2.4468%**	**4.0956%**	**4.8185%**	3.2335%
10	4.1055%	4.3734%	4.1284%	4.5632%	5.3558%	3.4572%
15	4.0098%	3.7497%	4.9345%	4.3230%	5.0695%	2.6726%
20	4.6115%	3.8454%	2.6438%	4.2597%	5.1349%	**2.6066%**
hidden neuron	**BRAZIL**	**GERMANY**	**AUSTRALIA**	**FRANCE**	**ITALY**	**SPAIN**
5	**3.1354%**	**4.0641%**	**3.3082%**	**4.6791%**	**4.6849%**	**4.7292%**
10	5.2411%	5.0720%	3.3496%	5.2291%	5.4034%	4.9348%
15	4.6445%	4.6191%	4.7678%	5.2152%	4.9562%	5.1372%
20	4.8961%	4.9767%	2.7879%	5.1556%	4.9787%	5.1303%

<u>Input lags</u>

In previous empirical studies of determining the training dataset length and hidden neurons, the input lags of trend and seasonal component are selected as 4 and 12 respectively. As the autocorrelation study in Figure 4 shows that the seasonal component is strongly autocorrelated of lag 12, we select 12 as the lag value for the seasonal component. For the trend component, we follow the configurations (5 neurons and training length 210 months) in previous discussion and study the performances of *p*NN models with 4, 8, and 12 input lags in Table 1. The performance comparison in the following Table 3 shows that the *p*NN models with input lag of 4 outperforms all other lag values consistently across all datasets.

Table 3 This table shows the average MAPE of three models, *p*NN-HP, *p*NN-WT, and *p*NN-MA, over all forecasting horizons under the configuration of 4, 8, and 12 input lags for trend component ARNN

input lag	MEXICO	CANADA	PRC	JAPAN	UK	KOREA
4	**3.9399%**	**3.4122%**	**2.6438%**	**4.0956%**	**4.8185%**	**3.2335%**
8	4.1475%	4.4152%	4.1380%	4.5642%	5.4324%	3.4675%
12	4.0153%	3.8022%	4.9850%	4.3492%	5.0979%	5.2058%
	BRAZIL	GERMANY	AUSTRALIA	FRANCE	ITALY	SPAIN
4	**3.1354%**	**4.0641%**	**3.3082%**	**4.6791%**	**4.6849%**	**4.7292%**
8	5.3028%	5.1131%	3.4046%	5.2797%	5.4464%	4.9352%
12	4.7021%	4.9972%	4.7809%	5.3087%	4.9657%	5.2088%

To summarize the empirical studies of the Part 1 evaluation, we have the *p*NN configuration as: 4 lags ARNN for trend component, 12 lags ARNN for seasonal component and the training dataset length of 210 months.

3.3.2 Part 2: Performance comparison

In this part, we follow the configurations of *p*NN-HP, *p*NN-WT, and *p*NN-MA models discussed in Section 3.3.1. We also evaluate the performances under different parameters heuristically as the traditional application. In *p*NN-HP model, the penalty parameter λ is selected as 100, 1600, 3600, and 129600, where the value of 100 is also the selection result by our method in Step 1 in Section 2.1. In the *p*NN-WT model, the wavelet transformation level is selected as 3, 4, 5, and 6, where level 3 is the selection result by our method. For *p*NN-MA, we only follow the configuration of MA with lag of 12 as the Figure 3(e,f) due to the discussion in Section 2.1.

The evaluation has two parts. Firstly, we estimate the *p*NN-HP, *p*NN-WT, and *p*NN-MA with the benchmark models ARIMA, ARFIMA, and SARIMA with the fixed length (210 months) of training dataset and test the forecasting performance of horizon from 1 to 18 months. In the second part, we estimate the models by the same length (210 months) of training dataset and evaluate the forecasting results, afterwards, we slide forward a window of 210 months by one-month step ahead and evaluate the forecasting results again. The training window will be slid until the testing horizon reaches the end of the dataset. This sliding window evaluation is not for enhancing the model performance but merely evaluate the model in a pseudo-practical context and compare the average performances across certain period. Those two parts cover a complete spectrum of the evaluation and show us a stable comparison result.

Part 1 results

The following Table 4 to Table 15 show the first part experiments results of the US tourist arrival from six source countries, Japan, P.R.China, Canada, Mexico, France and UK. The other six datasets (Korea, Brazil, Germany Australia, Italy, and Spain) are shown in the appendix. The performances of *p*NN-HP, *p*NN-WT and *p*NN-MA models with different parameters as well as ARIMA, ARFIMA, and SARIMA models are compared from horizon 1 to 18 months. In addition, the average performance over 18 horizons are also calculated and compared. As we observed from Table 4, Table 6, Table 8, Table 10, Table 12 and Table 14, pNN-HP with λ=100 achieves the best average MAPE compared with λ=100, 1600, 3600 and 129600 and *p*NN-WT with level 3 achieves the best average MAPE compared with other levels. This observation is consistent in all six datasets as well as the ones in the appendix. It shows the effectiveness of our proposed approach in Section 2. Therefore, an explicit decomposition with a stationary seasonal component and an unspecified non-linear trend component enhances the forecasting performance than the traditional heuristic selection of the decomposition parameters.

Among the pNN family models, the pNN-HP achieves slightly better performance than the pNN-WT in 12 datasets, where pNN-HP reaches a lower average MAPE than pNN-WT in eight datasets of Japan, P.R.China, Canada, UK, Korea, Brazil, Germany, and Australia while pNN-WT outperforms the pNN-HP in other four datasets. Both pNN-HP and pNN-WT reach a better performance than pNN-MA in all datasets. Similarly, in the Table 5,Table 7, Table 9, Table 11, Table 13, and Table 15, the SARIMA model outperforms the ARIMA and ARFIMA models consistently across all datasets. In most of the cases, SARIMA model achieves the average MAPE of 5% while the ARIMA and ARFIMA models achieve the average MAPE higher than 9%.

Table 4 This table shows the accuracy of monthly forecasts of US tourist arrivals from **Japan**. The Absolute Percentage Error (APE) is calculated at forecasting horizon 1 to 18 months (1.5 years). The *p*NN-HP, *p*NN-WT and *p*NN-MA models are all estimated by the data from Jan 1996 to Jun 2013 (210 months).

	*p*NN HP				*p*NN WT				*p*NN MA
horizon	100	1600	3600	129600	3	4	5	6	
1	1.2946%	1.3299%	1.2111%	1.9526%	0.9437%	1.4837%	1.3342%	0.9319%	4.5265%
2	1.3851%	1.4071%	1.4177%	1.2317%	1.7877%	1.3717%	1.3479%	1.4417%	0.5969%
3	0.9988%	1.7971%	2.2607%	1.8639%	0.8011%	1.9406%	1.0041%	0.8373%	1.9668%
4	2.7431%	2.8666%	2.9668%	2.7712%	0.9987%	2.7956%	2.5190%	2.5525%	0.7449%
5	2.5481%	2.5707%	2.8107%	2.5184%	2.6446%	2.8578%	2.6305%	2.7294%	3.7428%
6	2.4086%	2.3654%	2.4513%	2.0173%	2.6171%	1.7597%	1.8700%	2.1986%	4.0164%
7	2.7795%	2.8217%	2.8956%	2.0977%	2.5873%	2.3779%	2.7712%	2.2554%	2.4234%
8	2.0049%	1.3604%	1.7049%	2.5184%	2.5739%	1.8145%	1.4555%	2.4577%	2.4630%
9	3.8778%	2.8677%	3.9251%	2.7354%	3.3234%	3.0317%	3.8240%	2.6306%	1.5576%
10	3.7175%	3.9114%	3.8002%	3.7166%	3.6549%	3.8491%	3.8080%	3.6201%	2.8378%
11	3.6551%	4.2086%	4.1330%	3.9667%	4.3183%	3.7345%	3.7956%	4.9456%	2.9560%
12	4.0901%	4.0228%	3.9856%	3.8900%	4.2449%	4.0920%	5.9880%	5.8679%	9.1381%
13	5.7873%	5.6201%	5.8026%	5.4926%	5.8260%	5.8038%	5.5565%	5.4150%	11.2226%
14	6.1176%	6.1318%	6.1322%	6.3200%	6.6593%	6.1142%	6.1216%	6.3371%	3.8839%
15	5.7822%	6.0222%	5.6167%	6.8351%	5.2472%	6.5790%	6.7016%	6.2981%	7.4485%
16	6.2943%	6.9993%	6.9480%	6.9451%	6.8002%	7.3661%	7.1026%	6.4792%	4.3722%
17	6.2186%	7.3597%	7.2062%	7.1843%	7.4945%	7.5009%	7.1847%	7.0262%	10.9582%
18	6.7038%	7.3196%	7.2442%	6.7083%	6.4414%	6.4569%	7.4109%	7.0492%	8.5249%
Average	3.8004%	3.9434%	4.0285%	3.9314%	3.8313%	3.9405%	4.0237%	3.9485%	4.6322%

Table 5 This table shows the accuracy of monthly forecasts of US tourist arrivals from **Japan**. The Absolute Percentage Error (APE) is calculated at forecasting horizon 1 to 18 months (1.5 years). The ARFIMA, ARIMA, and SARIMA models are all estimated by the data from Jan 1996 to Jun 2013 (210 months).

horizon	ARFIMA	ARIMA	SARIMA
1	0.4865%	18.5198%	3.0922%
2	2.0643%	9.3111%	2.1239%
3	2.5707%	14.2966%	2.7580%
4	3.5864%	18.5518%	3.9179%
5	6.8951%	14.5906%	4.2308%
6	9.4675%	8.5771%	3.6135%
7	10.2902%	0.5218%	3.0747%
8	10.9009%	7.8582%	3.3738%
9	13.0405%	6.9061%	4.3382%
10	13.7182%	3.3191%	4.5412%
11	16.9740%	1.8422%	4.9572%
12	17.7309%	1.2963%	5.8497%
13	18.0973%	2.6266%	7.0228%
14	18.5660%	1.5557%	6.7218%
15	19.6086%	13.2230%	8.1238%
16	22.1751%	8.0824%	8.1422%

17	26.4561%	11.7477%	9.6670%
18	31.0637%	19.9274%	10.4409%
Average	13.5384%	9.0419%	5.3328%

Table 6 This table shows the accuracy of monthly forecasts of US tourist arrivals from **P.R.China**. The Absolute Percentage Error (APE) is calculated at forecasting horizon 1 to 18 months (1.5 years). The *p*NN-HP, *p*NN-WT and *p*NN-MA models are all estimated by the data from Jan 1996 to Jun 2013 (210 months).

	*p*NN HP				*p*NN WT				*p*NN MA
horizon	100	1600	3600	129600	3	4	5	6	
1	1.4738%	2.2359%	2.0059%	2.8848%	0.9956%	0.0812%	0.6563%	0.9732%	2.7280%
2	2.4523%	2.8736%	2.3594%	5.4266%	0.5300%	3.3011%	1.2894%	3.6583%	5.6464%
3	4.6712%	2.2179%	2.7901%	2.9574%	1.3336%	2.2560%	1.7138%	1.4117%	11.0425%
4	2.2918%	2.1086%	1.3180%	2.8814%	1.3688%	1.0805%	1.1245%	1.7318%	7.6005%
5	2.1485%	2.9594%	1.1641%	2.5909%	1.3180%	1.2627%	1.2153%	1.8928%	7.5157%
6	0.6943%	2.1607%	2.2778%	2.8697%	0.5464%	1.5500%	1.9015%	1.6624%	1.5161%
7	0.6677%	2.0638%	2.1727%	2.8963%	0.0542%	1.8700%	1.5801%	1.3611%	0.7167%
8	2.0986%	2.2919%	2.2944%	1.6247%	1.5961%	1.8676%	1.1848%	1.3858%	6.4989%
9	0.0362%	2.2517%	2.3559%	1.1620%	2.1071%	1.6034%	1.7449%	1.9099%	6.4290%
10	1.2598%	2.5191%	2.7276%	1.5526%	2.2008%	2.9325%	2.8823%	2.9619%	9.3558%
11	2.8297%	5.7708%	6.4601%	1.2873%	3.7010%	4.7387%	3.2893%	4.1472%	7.3130%
12	1.7281%	1.8603%	1.7315%	0.7695%	3.5486%	4.7882%	3.3827%	3.1286%	12.7059%
13	3.4168%	3.4886%	3.4277%	2.8247%	2.9467%	4.8015%	4.4521%	3.2130%	11.1119%
14	2.2418%	1.6473%	1.4741%	3.7678%	5.8597%	3.5690%	3.2767%	3.0562%	11.0950%
15	3.7302%	2.6282%	2.3762%	2.4691%	4.2891%	5.8927%	5.0202%	5.0731%	13.4263%
16	1.0693%	0.0094%	2.1627%	2.0201%	3.7017%	3.1070%	6.1266%	4.8330%	14.7797%
17	2.6976%	2.1397%	2.0130%	2.6595%	4.6959%	4.5980%	5.2372%	5.3744%	12.2693%
18	2.6046%	2.2771%	2.1770%	3.7490%	3.2764%	4.8806%	5.5901%	5.6262%	5.4539%
Average	2.1173%	2.4169%	2.4049%	2.5774%	2.4483%	3.0100%	2.8704%	2.9667%	8.1780%

Table 7 This table shows the accuracy of monthly forecasts of US tourist arrivals from **P.R.China**. The Absolute Percentage Error (APE) is calculated at forecasting horizon 1 to 18 months (1.5 years). The ARFIMA, ARIMA, and SARIMA models are all estimated by the data from Jan 1996 to Jun 2013 (210 months).

horizon	ARFIMA	ARIMA	SARIMA
1	2.8896%	1.3820%	1.6642%
2	3.8579%	1.0634%	2.9507%
3	6.8948%	1.3463%	3.5123%
4	7.4817%	2.7155%	2.8821%
5	9.0310%	3.9356%	3.1849%
6	13.9876%	4.7293%	3.0814%
7	14.5515%	4.9104%	2.9859%
8	18.5565%	5.5026%	4.0820%
9	18.9052%	8.2006%	4.2460%
10	19.6476%	12.7071%	5.5225%

11	22.8445%	13.2741%	6.8778%
12	28.5510%	14.3330%	6.9570%
13	29.9216%	14.5949%	7.6545%
14	30.3773%	16.4351%	7.5273%
15	34.7792%	16.5667%	8.7501%
16	35.5623%	23.8547%	8.8388%
17	39.8836%	27.2654%	9.8940%
18	43.0803%	34.1910%	10.2642%
Average	21.1557%	11.5004%	5.6042%

Table 8 This table shows the accuracy of monthly forecasts of US tourist arrivals from **Canada**. The Absolute Percentage Error (APE) is calculated at forecasting horizon 1 to 18 months (1.5 years). The *p*NN-HP, *p*NN-WT and *p*NN-MA models are all estimated by the data from Jan 1996 to Jun 2013 (210 months).

	*p*NN HP				*p*NN WT				*p*NN MA
horizon	100	1600	3600	129600	3	4	5	6	
1	0.5876%	0.7549%	0.8528%	1.8342%	1.3697%	1.4540%	0.3280%	0.4781%	5.0198%
2	1.6982%	2.0527%	2.0492%	0.3813%	1.0996%	2.7130%	1.3349%	0.5141%	4.9723%
3	0.8989%	1.1231%	2.0282%	1.2038%	1.4774%	1.8661%	1.3855%	1.2028%	0.0582%
4	1.4483%	2.2848%	1.6537%	1.6576%	1.8615%	1.4458%	1.7282%	1.6035%	2.4557%
5	1.2068%	2.6179%	2.4912%	2.1193%	1.5662%	1.9774%	1.7214%	2.1586%	3.5488%
6	0.9329%	2.7901%	2.5614%	1.6593%	2.0992%	1.8354%	2.0999%	1.7086%	5.9304%
7	0.6109%	1.4625%	1.2730%	1.2696%	2.3063%	2.5997%	2.2925%	1.2223%	2.2629%
8	1.2003%	2.2605%	1.9048%	1.6215%	2.5261%	2.8441%	2.3703%	1.6814%	0.9145%
9	0.2071%	2.9506%	2.7348%	3.1387%	2.9473%	3.7996%	2.3013%	3.2054%	2.2038%
10	0.1927%	3.8076%	3.4699%	4.1844%	2.7320%	3.6803%	3.0351%	4.2295%	3.9121%
11	0.2540%	3.9938%	3.8046%	4.0029%	3.6149%	3.8840%	3.2876%	3.5351%	4.2601%
12	0.2818%	2.6604%	2.7816%	3.1039%	3.6329%	4.1907%	4.7214%	3.4208%	9.7813%
13	1.5186%	4.7459%	4.3479%	6.0063%	4.7439%	4.9335%	5.8298%	6.1526%	9.6440%
14	2.5604%	6.7764%	6.1757%	6.1328%	4.1963%	5.6953%	5.4062%	5.1058%	9.4637%
15	2.9147%	6.7987%	6.1364%	5.4831%	5.2767%	5.7651%	5.6777%	5.6479%	8.3466%
16	3.4394%	5.7385%	5.4400%	6.6282%	5.6758%	5.2407%	5.3021%	6.7161%	8.0811%
17	3.4177%	6.2754%	5.8506%	6.4451%	5.8757%	6.2370%	6.5331%	6.6031%	8.3315%
18	3.6146%	6.2959%	6.0332%	7.3911%	5.8067%	6.4584%	6.2678%	6.8558%	10.9011%
Average	1.4992%	3.6328%	3.4216%	3.5702%	3.2671%	3.7011%	3.4235%	3.4467%	5.5604%

Table 9 This table shows the accuracy of monthly forecasts of US tourist arrivals from **Canada**. The Absolute Percentage Error (APE) is calculated at forecasting horizon 1 to 18 months (1.5 years). The ARFIMA, ARIMA, and SARIMA models are all estimated by the data from Jan 1996 to Jun 2013 (210 months).

horizon	ARFIMA	ARIMA	SARIMA
1	0.2743%	0.3820%	1.2123%
2	0.7676%	1.0634%	1.6951%
3	1.9123%	1.3463%	1.3184%
4	2.4996%	2.7155%	1.9413%
5	5.2153%	3.9356%	2.5962%
6	5.2406%	4.7293%	2.8716%

7	6.4020%	4.9104%	2.4193%
8	8.6295%	5.5026%	2.8596%
9	9.3311%	8.2006%	3.7291%
10	9.9407%	12.7071%	4.7174%
11	11.1286%	13.2741%	5.0036%
12	11.3902%	14.3330%	5.4816%
13	12.1584%	14.5949%	6.7887%
14	14.1502%	16.4351%	7.4634%
15	15.0727%	16.5667%	7.6078%
16	19.3988%	23.8547%	8.6832%
17	24.6458%	27.2654%	9.7710%
18	31.7562%	34.1910%	11.4156%
Average	10.5508%	11.4449%	4.8653%

Table 10 This table shows the accuracy of monthly forecasts of US tourist arrivals from **Mexico**. The Absolute Percentage Error (APE) is calculated at forecasting horizon 1 to 18 months (1.5 years). The *p*NN-HP, *p*NN-WT and *p*NN-MA models are all estimated by the data from Jan 1996 to Jun 2013 (210 months).

	*p*NN HP				*p*NN WT				*p*NN MA
horizon	λ=100	λ=1600	λ=3600	λ=129600	level 3	level 4	level 5	level 6	
1	1.0303%	0.7549%	0.8528%	1.8183%	1.2233%	1.0932%	0.4273%	0.5396%	1.6852%
2	1.3432%	2.0527%	2.0492%	2.4463%	1.8404%	2.1276%	1.4575%	1.4531%	4.0865%
3	1.4270%	1.1231%	2.0282%	0.6498%	1.0411%	2.1061%	1.0590%	1.3539%	2.0481%
4	1.6341%	2.2848%	1.6537%	2.6260%	1.6634%	2.7180%	2.7834%	2.1080%	5.1358%
5	1.8037%	2.6179%	2.4912%	3.8036%	1.6326%	3.7678%	2.3031%	2.6332%	4.3871%
6	2.0126%	2.7901%	2.5614%	4.3407%	1.0443%	3.4638%	2.8478%	2.5143%	1.5918%
7	1.1602%	1.4625%	1.2730%	3.1781%	1.3287%	3.4083%	2.3047%	2.8762%	0.5056%
8	2.4166%	2.2605%	1.9048%	3.4777%	1.2940%	3.8321%	2.9106%	2.2913%	0.3607%
9	1.6581%	2.9506%	2.7348%	4.2646%	1.4287%	4.5479%	3.4219%	3.8964%	2.3973%
10	2.7440%	3.8076%	3.4699%	4.8321%	1.8148%	5.3376%	4.3598%	4.9320%	0.2436%
11	3.2269%	3.9938%	3.8046%	5.2973%	1.7748%	5.2688%	4.4136%	4.7927%	2.6506%
12	2.4804%	2.6604%	2.7816%	4.8132%	1.8505%	5.3872%	4.2595%	4.3876%	4.8089%
13	4.5861%	4.7459%	4.3479%	5.5715%	2.8987%	5.9117%	5.4460%	4.2619%	3.2915%
14	5.8705%	6.7764%	6.1757%	8.6470%	4.0512%	5.2926%	5.9064%	5.7734%	7.3471%
15	5.6514%	6.7987%	6.1364%	7.4945%	4.6904%	6.5939%	5.3693%	5.3088%	5.8922%
16	5.4679%	5.7385%	5.4400%	7.3922%	5.6796%	6.4421%	5.1079%	5.6051%	5.3964%
17	5.1059%	6.2754%	5.8506%	9.0279%	5.7356%	7.0455%	7.2478%	7.0145%	13.2501%
18	6.6773%	6.2959%	6.0332%	8.5478%	7.1605%	7.3730%	7.7003%	7.0234%	6.9257%
Average	3.1276%	3.6328%	3.4216%	4.8664%	2.4856%	4.5782%	3.8249%	3.8252%	4.0002%

Table 11 This table shows the accuracy of monthly forecasts of US tourist arrivals from **Mexico**. The Absolute Percentage Error (APE) is calculated at forecasting horizon 1 to 18 months (1.5 years). The ARFIMA, ARIMA, and SARIMA models are all estimated by the data from Jan 1996 to Jun 2013 (210 months).

horizon	ARFIMA	ARIMA	SARIMA

1	1.5598%	9.4306%	1.8559%
2	3.3231%	6.2667%	2.5860%
3	5.9260%	8.8243%	2.5079%
4	14.2209%	13.9717%	4.6182%
5	14.6464%	16.0893%	5.1069%
6	15.1554%	10.7261%	4.4589%
7	16.0494%	19.3084%	4.8050%
8	16.6518%	14.9878%	4.7625%
9	17.9664%	24.2640%	6.3210%
10	18.6219%	20.0341%	6.3816%
11	19.4014%	23.0710%	7.0632%
12	21.9862%	34.7013%	8.1924%
13	23.0783%	36.2280%	9.1243%
14	23.6760%	31.1101%	10.0570%
15	27.8694%	26.6214%	9.8569%
16	29.6739%	27.5956%	9.9581%
17	30.4218%	30.8445%	11.6200%
18	37.8498%	38.5734%	12.7418%
Average	18.7821%	21.8138%	6.7598%

Table 12 This table shows the accuracy of monthly forecasts of US tourist arrivals from **France**. The Absolute Percentage Error (APE) is calculated at forecasting horizon 1 to 18 months (1.5 years). The *p*NN-HP, *p*NN-WT and *p*NN-MA models are all estimated by the data from Jan 1996 to Jun 2013 (210 months)

	*p*NN HP				*p*NN WT				*p*NN MA
horizon	100	1600	3600	129600	3	4	5	6	
1	3.2027%	4.1723%	3.4533%	5.2630%	0.9478%	6.0442%	4.5824%	4.6654%	12.6512%
2	1.5821%	2.4158%	0.6651%	2.3053%	1.3434%	3.3115%	2.2900%	2.1426%	0.4667%
3	0.7468%	1.1671%	0.6886%	2.2894%	1.7170%	2.3978%	2.4377%	2.1139%	2.5901%
4	1.2826%	0.4886%	1.0397%	1.1068%	0.9280%	1.3175%	0.8926%	2.7692%	1.2201%
5	2.5993%	2.1395%	2.1628%	2.0750%	2.0602%	2.9168%	1.9423%	2.2033%	8.4099%
6	2.6886%	2.4382%	2.3765%	2.2685%	0.4719%	3.0303%	2.2940%	2.8161%	5.7287%
7	4.2706%	4.1083%	4.0246%	3.4881%	2.2615%	4.2408%	3.9043%	2.9176%	3.9227%
8	2.3922%	4.1707%	4.0328%	3.8053%	3.9929%	3.4214%	3.6045%	3.1091%	2.7618%
9	3.9190%	2.9572%	2.8016%	3.4686%	3.9666%	4.0980%	3.7945%	3.0317%	8.8035%
10	3.8011%	4.0665%	3.8909%	3.3178%	4.4975%	4.8297%	4.0877%	3.4178%	2.6140%
11	2.7181%	2.6640%	2.3041%	2.0697%	4.2153%	6.1107%	2.2561%	3.9401%	8.2364%
12	3.2637%	2.8801%	2.6060%	2.0367%	3.8353%	5.7709%	3.8882%	4.5028%	11.5365%
13	7.9898%	8.6338%	9.2439%	7.5091%	5.9379%	10.8231%	8.4801%	8.6239%	12.5583%
14	7.0039%	8.4351%	4.7674%	2.8099%	6.6998%	8.9735%	7.5532%	7.3956%	3.7810%
15	5.8007%	6.9195%	5.4257%	4.8649%	5.8841%	6.0714%	5.6052%	4.2967%	3.5145%
16	5.4728%	5.4108%	5.3075%	4.4898%	4.6002%	5.4515%	5.4583%	4.4602%	7.4224%
17	6.5138%	6.6733%	5.9333%	5.6390%	4.8447%	6.6754%	6.4543%	5.5396%	12.4412%
18	7.2474%	6.1522%	6.7785%	5.2820%	3.6605%	7.6003%	7.3551%	6.1803%	11.6435%
Average	4.0275%	4.2163%	3.7501%	3.5605%	3.4369%	5.1714%	4.2711%	4.1181%	6.6835%

Table 13 This table shows the accuracy of monthly forecasts of US tourist arrivals from **France**. The Absolute Percentage Error (APE) is calculated at forecasting horizon 1 to 18 months (1.5 years). The ARFIMA, ARIMA, and SARIMA models are all estimated by the data from Jan 1996 to Jun 2013 (210 months).

horizon	ARFIMA	ARIMA	SARIMA
1	0.0563%	0.2287%	4.1152%
2	4.3767%	3.0465%	2.1769%
3	3.8329%	3.1798%	2.1056%
4	3.2855%	4.3094%	1.6945%
5	7.9836%	7.8926%	3.8532%
6	9.4953%	8.1076%	3.7923%
7	5.7207%	10.1122%	4.4519%
8	14.1408%	16.0817%	5.5921%
9	17.0210%	17.5074%	6.4881%
10	16.4819%	18.4163%	6.3110%
11	24.3493%	19.2968%	7.1055%
12	22.8291%	20.0931%	7.5675%
13	22.7435%	22.7652%	11.3917%
14	27.0123%	27.0609%	10.1357%
15	28.3679%	27.4863%	9.4761%
16	30.4069%	29.7150%	9.8359%
17	65.1216%	68.4182%	17.6595%
18	54.7041%	79.3608%	17.8150%
Average	19.8850%	21.2821%	7.3093%

Table 14 This table shows the accuracy of monthly forecasts of US tourist arrivals from **UK**. The Absolute Percentage Error (APE) is calculated at forecasting horizon 1 to 18 months (1.5 years). The *p*NN-HP, *p*NN-WT and *p*NN-MA models are all estimated by the data from Jan 1996 to Jun 2013 (210 months).

	*p*NN HP				*p*NN WT				*p*NN MA
horizon	100	1600	3600	129600	3	4	5	6	
1	0.9547%	0.9703%	1.2032%	2.5245%	3.1530%	1.9045%	0.5826%	1.3244%	5.9264%
2	2.2935%	2.6239%	0.1954%	2.7551%	2.9137%	2.3669%	0.3438%	0.0441%	6.1367%
3	1.4011%	1.3260%	1.2719%	1.4380%	2.3437%	1.8266%	1.0823%	1.7709%	3.8952%
4	2.0866%	1.9839%	1.9607%	2.0994%	1.8423%	2.0276%	2.0479%	2.0634%	0.7739%
5	2.3143%	1.8793%	1.9107%	2.0739%	2.2916%	2.2884%	1.8675%	2.0137%	5.9894%
6	2.1185%	2.0289%	1.9863%	2.0821%	2.4278%	2.0422%	2.9585%	2.1163%	1.9572%
7	2.8650%	2.2785%	3.0442%	2.8512%	3.3154%	2.1144%	3.0528%	2.2176%	3.4049%
8	1.9981%	1.8580%	2.1376%	2.2103%	3.0231%	2.3600%	3.1660%	3.4752%	6.6162%
9	2.7481%	2.7443%	3.8459%	3.9382%	3.0014%	2.5530%	3.6269%	3.7656%	5.1520%
10	4.4985%	4.5747%	4.4488%	4.3688%	4.4276%	4.5775%	4.5666%	4.3854%	5.4701%
11	3.2113%	3.1344%	4.5367%	2.7828%	4.8426%	4.8023%	4.4725%	5.7785%	2.8929%
12	3.6058%	3.6662%	3.6658%	3.5160%	3.1510%	4.5092%	3.5953%	5.2182%	9.6593%
13	8.4892%	7.8067%	8.4763%	8.4566%	4.4954%	6.9303%	7.8755%	6.4571%	9.0916%
14	7.4250%	7.3572%	7.3968%	8.4128%	8.4563%	7.2718%	7.8028%	7.9026%	12.6569%
15	5.9657%	5.9083%	5.8144%	6.0798%	5.1101%	7.9106%	7.9521%	7.0552%	6.6408%

16	6.5030%	6.4474%	6.4590%	6.5717%	5.8122%	7.2904%	7.3641%	7.4789%	4.0742%
17	6.7170%	6.1681%	6.2723%	6.3987%	6.6048%	7.0164%	7.3215%	7.3525%	11.3040%
18	6.8986%	6.9548%	6.9443%	6.8136%	6.6704%	7.7903%	7.8878%	7.8924%	6.1590%
Average	4.0052%	3.8728%	3.9761%	4.1874%	4.1046%	4.3101%	4.3092%	4.3507%	5.9889%

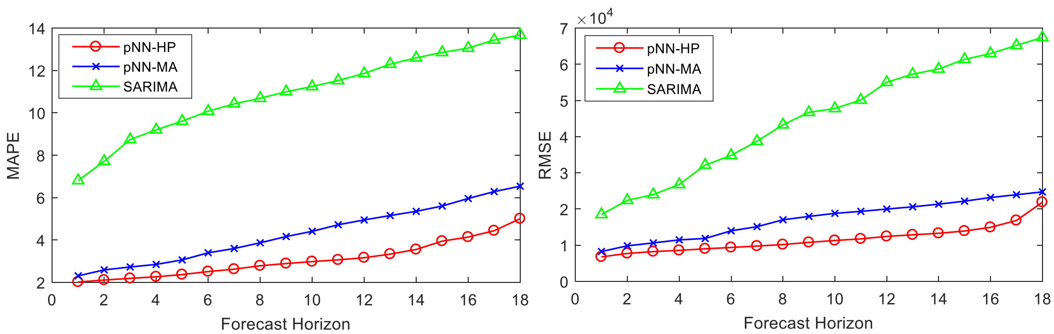
Table 15 This table shows the accuracy of monthly forecasts of US tourist arrivals from **UK**. The Absolute Percentage Error (APE) is calculated at forecasting horizon 1 to 18 months (1.5 years). The ARFIMA, ARIMA, and SARIMA models are all estimated by the data from Jan 1996 to Jun 2013 (210 months).

horizon	ARFIMA	ARIMA	SARIMA
1	0.8388%	3.0939%	2.0433%
2	1.7065%	0.7434%	2.0112%
3	2.1569%	0.5093%	1.7293%
4	2.3598%	3.2640%	2.0463%
5	2.7858%	2.2572%	2.5156%
6	3.0822%	4.0884%	2.4444%
7	3.6274%	6.3438%	3.1923%
8	4.5189%	15.6542%	4.2743%
9	7.3903%	10.0052%	4.4337%
10	7.5344%	4.9507%	4.8912%
11	8.6988%	7.2183%	4.7610%
12	9.5324%	5.9929%	5.1011%
13	16.0177%	19.1206%	9.3834%
14	22.4998%	27.2351%	11.3106%
15	26.7107%	23.2183%	9.8515%
16	36.8453%	41.1896%	12.3669%
17	51.7933%	74.1898%	17.3762%
18	64.7718%	69.1361%	17.9927%
Average	15.1595%	17.6784%	6.5403%

Part 2 results

As discussed before, the second part evaluation is to show an average performance based on sliding window. As the experimental evaluation in Part 1 shows that the *p*NN-HP model is slightly better than *p*NN-WT and SARIMA outperforms the other two traditional models, in this part, we select *p*NN-HP, *p*NN-MA and SARIMA models for the further evaluation. The Figure 11 shows the average MAPE and the RMSE error measures of the 12 tourist arrival series across all forecasting horizons. It is obviously and consistently that the *p*NN type models achieve the highest performance throughout all horizons from h=1 to 18 (1 month to 1.5 years). The forecasting performance of SARIMA model is significantly lower than either the *p*NN-HP or the *p*NN-MA model.

Usually, in the seasonal data forecasting, the data from the same season of previous cycles (i.e., years) is more informative than that from the most recent ones. Due to the study by (Song, Smeral, G. Li, & Chen, 2013), a 12-month lag of seasonal model in equation (2) can capture seasonal patterns well in forecasting the seasonal component of the monthly tourist arrival series. In addition, the strong capability of ARNN in capturing the non-linearity offers a significantly lower error in forecasting the trend components as the examples in Figure 5, where the Absolute Percentage Errors (APE) is 2% in (b) at the most. It is obviously that the ARNN is the key in achieving forecasting precision and underlines our contribution to the literature.



(a) (b)

Figure 11 This figure shows the Mean Average Absolute Percentage Error (MAPE) and Root Mean Square Error (RMSE) by different horizon. The MAPE and RMSE measures are averaged across 12 market cases. The data of each single market is shown in Table 16 to Table 21. *p*NN-HP is the paired Neural Network model with HP filter; *p*NN-MA is the paired Neural Network with Moving Average as the trend filter; SARIMA is the Seasonal Autoregressive Integrated Moving Average.

Figure 12 provides a detailed insight into the forecast accuracy. The forecast results of horizon h=1 to 18 (1 month to 1.5 years) with six selected source market data including Japan, China Mainland, Canada, Mexico, France and UK are presented. As shown in Figure 12, the SARIMA model performs the worst with all data except China Mainland, where the forecast of SARIMA is the closest to the one of pNN models. We can also observe that the *p*NN-HP model usually outperforms the *p*NN-MA model in some examples, although in most cases they perform quite similarly. This follows our two expectations: 1) the ARNN enhances the overall performance of *p*NN type models; 2) the slightly more non-linearity of the trend by moving average than that of the trend by HP filter (as the illustration in Figure 5(b)) brings the slightly higher error rate of *p*NN-MA than that of *p*NN-HP, though they both achieve high accuracy compared to SARIMA model.

One of the motivation to propose *p*NN type model is to explicitly decompose the trend and the seasonal component and model and forecast them by the models that can capture the corresponding feature the best. ARNN is strong in capturing trend in time series (Zhang & Qi, 2005) (Patil, Tantau, & Salokhe, 2008) as well as the cyclical patterns. Therefore, our *p*NN type model takes advantage of the strong capability of the ARNN on the components separately. Unlike the traditional application of neural network on tourism area, which usually simply feeds the original data to the model and generates the result, our proposed *p*NN enhances the overall performance by the specifically modelling different features, which are explicitly decomposed by HP filter or moving average.

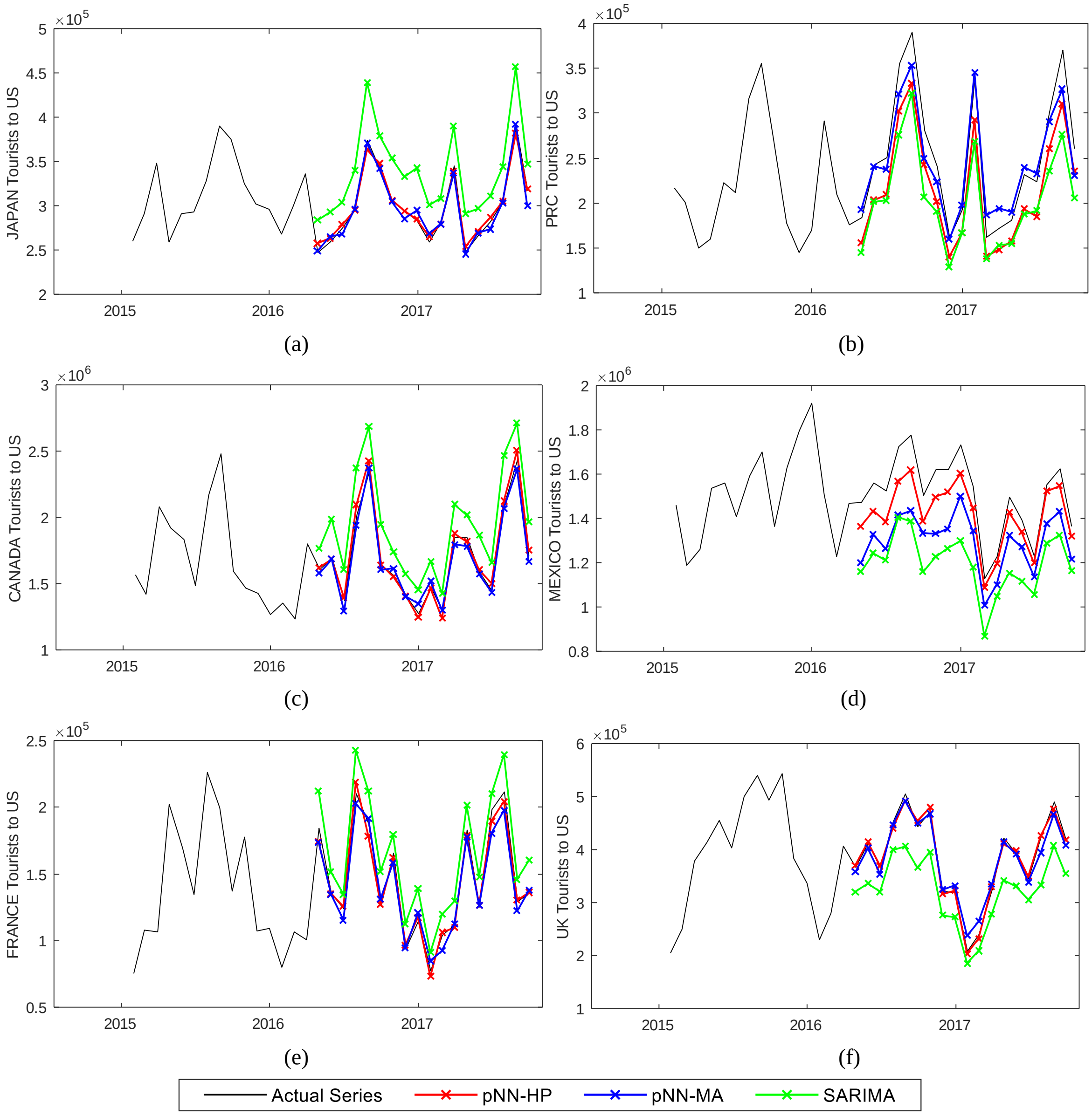
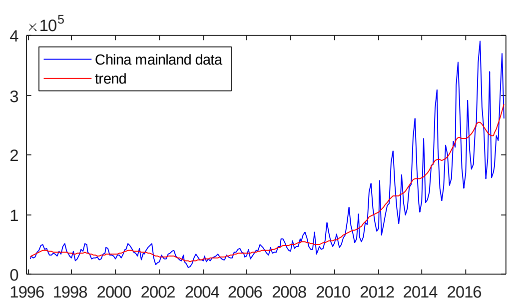
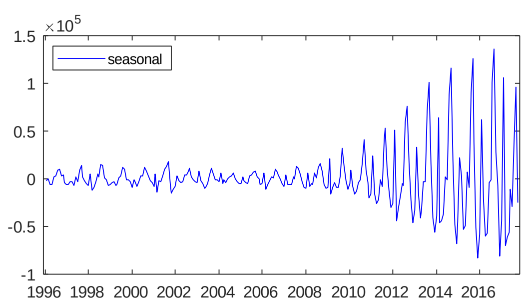


Figure 12 This figure shows the forecasting results of tourist arrivals from six source markets (Japan, China Mainland, Canada, Mexico, France and UK) by three models: *p*NN-HP, *p*NN-MA, and SARIMA. The models are estimated by the data from Jan 1996 up to Mar 2016, which is partially illustrated for the clarity of the figures. The forecasting results are up to 18 months from Apr 2016 to Sep 2017. Note: pNN-HP is the paired Neural Network with HP filter; *p*NN-MA is the paired Neural Network model with Moving Average as the trend filter; SARIMA is the Seasonal Autoregressive Integrated Moving Average.

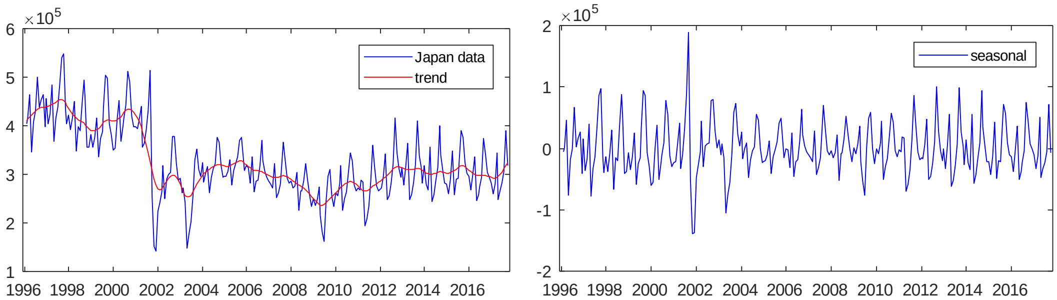
In additional to the original results in Figure 12, the monthly forecast error measures of tourist arrivals data across all horizons from six source markets are shown as selected examples in Table 16 to Table 21. Even without any statistical comparison, it is clear that the *p*NN type models significantly outperform the competing model SARIMA. The performance of *p*NN type models is consistent across all horizons. However, *p*NN type models perform differently across all source market data. For example, the highest MAPE in Table 16 to Table 21 for *p*NN-HP model is 6.2882% in tourist arrival data from China mainland. However, the lowest MAPE for *p*NN-HP model is merely 2.6644% in Japan tourist data. We observe dramatically different patterns of the two series of Japan and China mainland in Figure 13. The tourist arrival from Japan is relatively stable except a big drop in 2001 due to the '911' event. From 2010 to 2017, the tourist arrival from Japan shows relatively similar repeated patterns. However, the tourist arrival from China mainland shows a roughly 800% increase from 0.5×10^5 in 1996 to 4×10^5 2017. From 1996 to 2008, both the trend and seasonal components are stable. After 2008, however, the trend component shows a quick increase while the seasonal component shows an annual oscillation with divergent magnitude. Such patterns kill the precision of the autoregressive models in equation (2) and contribute to the relatively large forecasting error. We found that the average absolute percentage error (APE) of the forecast trend and seasonal components of China mainland tourist arrivals in Figure 13(a) and (b) are 2.94% and 9.54% respectively while the ones of Japan tourist arrivals in Figure 13(c) and (d) are 1.73% and 4.21% respectively. Therefore, the divergent changes in seasonal component of China mainland data is the key reason for a relatively low precision in pNN model. However, we also notice that the tourist arrival data from China mainland to US is a special case due to the "opening up policy" in China mainland especially after 2008, when Beijing successfully hosted the Games of the XXIX Olympiad. Even though, the pNN type model still outperforms the traditional SARIMA model, which also achieves the highest MAPE of 19.7615% with China mainland tourist data.



(a)



(b)



(c) (d)

Figure 13 This figure shows a comparison of the US tourist arrival data; from Japan and China mainland. (a) the tourist arrival data from China mainland and the trend component is extracted by HP filter; (b) the seasonal component of China mainland tourist to US; (c) the tourist arrival data from Japan and the trend component is extracted by HP filter; (d) the seasonal component of Japan tourist to US.

Table 16 This table shows the average accuracy of monthly forecasts of US tourist arrivals from Japan. The MAPE and RMSE are average values across all forecasted data from Aug 2013 to Sep 2017. The models are all estimated by the data from Jan 1996 to Jul 2013.

JAPAN	MAPE (%)			RMSE		
Horizon	pNN-HP	pNN-MA	SARIMA	pNN-HP	pNN-MA	SARIMA
1	1.4181	2.0708	5.7228	4,054.2216	5,947.8787	62.8926
2	1.4251	2.1153	6.3176	4,116.4230	6,020.8353	810.7105
3	1.4387	2.2448	6.3184	4,940.8339	6,933.7099	2,194.7941
4	1.4761	2.2996	6.8054	4,970.5450	7,182.1324	2,937.8717
5	1.4971	2.4668	7.1076	4,999.1695	7,203.4253	3,151.1202
6	1.6709	2.5655	7.4185	5,221.7649	7,458.9450	4,072.9544
7	1.6711	2.5902	7.4944	5,274.6463	7,632.7029	5,474.6889
8	1.9163	2.6175	7.7514	5,350.2330	7,829.8352	6,815.6600
9	1.9649	2.7587	7.7540	5,353.7903	7,986.5011	8,266.6955
10	1.9809	2.8478	8.0971	5,713.3339	8,051.9947	8,270.2917
11	1.9975	2.8738	8.2193	5,758.4859	8,114.1258	8,355.9751
12	2.0234	2.8808	8.5103	6,248.8423	8,454.1336	9,085.0629
13	2.2615	3.0187	8.5690	6,691.2576	8,626.6082	9,227.3149
14	2.2837	3.0473	8.8332	6,799.8298	9,686.8360	10,743.7732
15	2.3124	3.1867	8.8431	6,936.5144	9,788.7525	11,743.7681
16	2.3790	3.3717	8.9026	6,949.0603	9,842.7553	12,381.1422
17	2.6283	3.6827	9.1883	7,808.9009	10,981.2925	12,508.8093
18	2.6644	3.8045	9.2174	8,826.8160	11,741.7673	16,898.2777

Note: MAPE is Mean Average Absolute Percentage Error; RMSE is Root Mean Square Error; pNN-HP is the paired Neural Network model with HP filter; pNN-MA is the paired Neural Network model with Moving Average as the trend filter; SARIMA is the Seasonal Autoregressive Integrated Moving Average.

Table 17 This table shows the average accuracy of monthly forecasts of US tourist arrivals from P.R.China. The MAPE and RMSE are average values across all forecasted data from Aug 2013 to Sep 2017. The models are all estimated by the data from Jan 1996 to Jul 2013.

P.R.China	MAPE (%)			RMSE		
Horizon	pNN-HP	pNN-MA	SARIMA	pNN-HP	pNN-MA	SARIMA
1	2.1939	2.6700	8.7477	3,389.4265	3,867.8937	4,049.8029
2	2.2354	2.7582	9.4069	3,535.8994	5,363.7645	11,281.2351
3	2.3853	2.9167	13.0022	3,608.4120	6,167.2981	24,672.1346
4	2.5095	3.2158	13.0057	3,679.6287	6,960.3408	30,046.6383
5	2.8493	3.4330	13.6666	3,851.8719	7,357.0434	31,547.1361
6	2.8788	3.6580	14.5056	4,464.0106	7,685.4256	34,010.5799
7	3.0546	4.5565	15.3433	5,080.0699	8,326.3558	38,043.4560

8	3.6452	4.9174	15.4939	5,406.6520	8,777.0933	41,296.2372
9	4.0254	4.9781	16.5549	5,492.1599	9,142.2132	44,048.4914
10	4.3749	5.0052	16.5588	5,556.7633	10,562.9857	44,741.0216
11	4.5822	5.5689	16.7300	6,458.7721	12,049.3078	47,762.3227
12	4.6617	5.6944	16.9114	9,245.5575	12,343.0974	52,517.3111
13	4.8025	6.1542	17.2186	9,719.7594	12,744.8141	55,204.0855
14	4.8565	6.8230	17.3124	10,366.2691	14,315.0753	62,205.1557
15	5.8348	7.6449	17.5534	12,210.8285	16,494.3540	62,622.7461
16	6.0910	8.7256	18.1220	13,664.4354	17,081.6246	63,741.2330
17	6.1872	9.1358	19.3662	15,102.8313	20,231.3794	73,226.0433
18	6.2882	10.2183	19.7615	15,812.8968	20,998.1905	77,462.0883

Note: MAPE is Mean Average Absolute Percentage Error; RMSE is Root Mean Square Error; pNN-HP is the paired Neural Network model with HP filter; pNN-MA is the paired Neural Network model with Moving Average as the trend filter; SARIMA is the Seasonal Autoregressive Integrated Moving Average.

Table 18 This table shows the average accuracy of monthly forecasts of US tourist arrivals from Canada. The MAPE and RMSE are average values across all forecasted data from Aug 2013 to Sep 2017. The models are all estimated by the data from Jan 1996 to Jul 2013.

CANADA	MAPE (%)			RMSE		
Horizon	pNN-HP	pNN-MA	SARIMA	pNN-HP	pNN-MA	SARIMA
1	1.9035	2.0288	6.3349	29,574.0551	29,115.2496	23,612.7614
2	1.9213	2.0366	7.2566	31,639.8449	32,423.3141	24,007.5529
3	1.9998	2.0508	7.6164	32,997.5614	33,268.1662	25,359.8193
4	2.0176	2.0985	7.8078	34,349.9232	37,737.8413	35,513.7028
5	2.1590	2.2578	8.3842	34,652.0709	38,551.6398	40,877.8516
6	2.1766	2.4782	8.7882	34,838.0449	40,927.5715	46,406.3002
7	2.1797	2.5653	8.8957	36,389.6919	46,293.5134	56,914.8491
8	2.2958	2.8336	9.1857	38,467.9057	53,846.6558	57,658.1449
9	2.4023	2.9751	9.2372	42,776.4385	54,351.7902	67,248.5746
10	2.5649	3.2464	9.3832	44,424.6116	55,052.8761	70,715.0143
11	2.6107	3.4492	9.3946	44,483.5258	56,376.6186	73,552.7092
12	2.7096	3.4499	9.5989	46,719.3535	59,543.0840	81,403.3225
13	2.7706	3.6082	9.6609	46,869.1387	59,832.5781	92,093.2720
14	2.9847	3.8336	10.5681	48,633.3919	61,402.9161	92,634.6652
15	3.2304	4.1664	11.3036	50,546.9690	62,518.2238	107,550.8504
16	3.4763	4.2384	11.3063	55,964.3055	66,041.3895	109,282.2452
17	3.9160	4.3333	11.3895	69,943.1255	66,111.7145	113,239.4456
18	4.7323	4.5588	11.4530	117,251.7355	70,288.0321	117,940.9077

Note: MAPE is Mean Average Absolute Percentage Error; RMSE is Root Mean Square Error; pNN-HP is the paired Neural Network model with HP filter; pNN-MA is the paired Neural Network model with Moving Average as the trend filter; SARIMA is the Seasonal Autoregressive Integrated Moving Average.

Table 19 This table shows the average accuracy of monthly forecasts of US tourist arrivals from Mexico. The MAPE and RMSE are average values across all forecasted data from Aug 2013 to Sep 2017. The models are all estimated by the data from Jan 1996 to Jul 2013.

MEXICO	MAPE (%)			RMSE		
Horizon	pNN-HP	pNN-MA	SARIMA	pNN-HP	pNN-MA	SARIMA
1	2.0551	3.1615	8.4908	23,008.9286	35,896.4678	76,226.3350
2	2.1493	3.1794	11.0394	30,034.8306	45,076.1205	92,581.4979
3	2.2997	3.6235	12.2315	32,120.5691	49,137.0452	124,978.4799
4	2.3816	3.6724	13.2957	32,689.2784	51,805.6269	206,210.6986
5	2.3954	3.7165	13.5651	35,360.0412	54,152.3174	255,924.4047
6	2.4068	6.1008	14.3385	37,918.8539	74,973.5001	273,460.8150
7	2.5992	6.5296	14.7181	38,737.2888	80,005.6105	297,826.1855
8	2.6431	6.9635	14.7415	39,970.9958	93,468.5149	334,180.7186
9	2.6603	7.1458	14.8651	41,492.9709	98,001.1533	350,517.8578
10	2.7547	7.1770	15.1530	43,861.5262	102,553.8870	352,985.4123
11	2.9492	7.2857	15.2746	45,512.4265	103,310.2356	357,304.6869

12	2.9575	7.3130	15.6239	46,122.7767	105,057.1264	392,696.8724
13	3.0117	7.7906	15.8549	46,799.1201	105,735.4548	402,176.7511
14	3.1128	7.8629	16.3022	47,804.7792	107,459.8577	406,559.9869
15	3.2467	7.8649	16.5410	48,535.5247	110,370.2890	415,238.6482
16	3.3036	8.1077	16.7006	49,214.1087	114,738.5518	419,592.4298
17	3.5934	8.1079	16.7132	50,539.1630	116,850.5917	424,200.9279
18	3.6229	8.1335	16.9801	54,686.8468	119,028.1019	430,970.4110

Note: MAPE is Mean Average Absolute Percentage Error; RMSE is Root Mean Square Error; pNN-HP is the paired Neural Network model with HP filter; pNN-MA is the paired Neural Network model with Moving Average as the trend filter; SARIMA is the Seasonal Autoregressive Integrated Moving Average.

Table 20 This table shows the average accuracy of monthly forecasts of US tourist arrivals from FRANCE. The MAPE and RMSE are average values across all forecasted data from Aug 2013 to Sep 2017. The models are all estimated by the data from Jan 1996 to Jul 2013.

FRANCE	MAPE (%)			RMSE		
Horizon	pNN-HP	pNN-MA	SARIMA	pNN-HP	pNN-MA	SARIMA
1	2.0968	2.6193	8.1461	2,204.1445	2,583.0345	2,787.1725
2	2.1712	3.3467	9.1114	2,321.2121	3,559.6996	5,871.9584
3	2.2151	3.6270	10.7600	2,441.6981	4,545.7766	14,876.8553
4	2.2767	3.7776	11.3432	2,478.8577	4,770.9112	16,543.2730
5	2.3220	5.2181	11.4788	3,017.5703	4,847.1334	17,364.3711
6	2.5546	5.3940	12.2371	3,054.1489	5,440.8341	18,519.9672
7	2.6189	5.4629	12.3979	3,187.0396	5,883.8394	20,226.9403
8	2.7427	5.6700	12.6864	3,240.0692	6,090.0635	22,121.0034
9	2.8423	5.7421	13.1152	3,460.5369	6,735.7209	24,832.6736
10	2.8521	5.7862	13.5528	3,502.2232	7,284.6118	25,671.8729
11	3.0307	6.2567	14.0838	3,546.2541	8,493.6410	27,960.8082
12	3.2129	6.3154	14.6017	4,547.2265	8,643.9093	28,581.9237
13	3.2134	6.3256	15.7236	4,788.6029	9,078.5282	28,688.1238
14	3.4172	6.9927	15.7812	4,809.2516	10,274.5840	29,176.0713
15	3.5129	7.0585	15.8486	5,351.4803	10,315.5725	30,310.6195
16	3.6808	8.1430	15.8984	5,949.9461	10,368.8115	31,245.8847
17	3.8886	8.2036	16.0508	6,418.1043	10,462.3922	32,360.6636
18	4.0212	8.2543	16.1345	6,530.2179	10,671.9451	32,633.9539

Note: MAPE is Mean Average Absolute Percentage Error; RMSE is Root Mean Square Error; pNN-HP is the paired Neural Network model with HP filter; pNN-MA is the paired Neural Network model with Moving Average as the trend filter; SARIMA is the Seasonal Autoregressive Integrated Moving Average.

Table 21 This table shows the average accuracy of monthly forecasts of US tourist arrivals from UK. The MAPE and RMSE are average values across all forecasted data from Aug 2013 to Sep 2017. The models are all estimated by the data from Jan 1996 to Jul 2013.

UK	MAPE (%)			RMSE		
Horizon	pNN-HP	pNN-MA	SARIMA	pNN-HP	pNN-MA	SARIMA
1	2.0125	2.0136	6.0649	5,905.0835	6,811.1439	365.4765
2	2.0292	2.0192	6.2400	6,394.6941	7,184.9834	459.0899
3	2.1592	2.0834	6.8939	7,055.4306	8,102.3625	2,735.7885
4	2.1748	2.1805	7.6881	7,914.8472	8,925.2220	4,089.6066
5	2.3482	2.2493	8.0631	8,553.7269	9,114.8483	4,516.5265
6	2.6110	2.4806	8.2551	8,553.8564	9,160.5909	4,824.4235
7	2.6127	2.6586	8.7022	9,470.1553	9,992.9597	6,131.5844
8	2.7743	2.9626	8.8264	9,484.3761	10,021.0201	8,507.2936
9	2.8075	3.0014	8.9665	9,522.9954	10,109.8395	10,287.9342
10	2.8297	3.7035	9.0428	10,405.7139	11,812.6566	11,472.7231
11	2.8436	3.8187	9.1872	10,583.7699	11,866.8348	15,061.4749
12	3.1550	3.9078	9.2531	10,797.7889	12,275.2218	15,151.2231
13	3.5197	4.0512	9.8970	12,552.6999	12,801.4114	16,132.8664
14	3.7874	4.1160	9.9473	12,601.5293	13,098.4995	16,573.6554
15	3.9738	4.2072	10.2926	13,862.9409	14,147.0197	16,864.2814

16	4.0694	4.2164	10.2984	14,115.8330	15,423.6550	22,046.4316
17	4.3471	5.1342	10.6998	16,254.6417	16,217.2473	22,457.6025
18	5.2968	5.6525	10.7351	16,629.8387	16,722.6244	23,874.5622

Note: MAPE is Mean Average Absolute Percentage Error; RMSE is Root Mean Square Error; pNN-HP is the paired Neural Network model with HP filter; pNN-MA is the paired Neural Network model with Moving Average as the trend filter; SARIMA is the Seasonal Autoregressive Integrated Moving Average.

4. Conclusion

The fact that tourism data comprises both a long-term trend component and a strong repeated seasonal component has crucial implications for modelling and forecasting tourism data over both short and long horizons. In this paper, we combine the ideas from the work in (Harvey & Todd, 1983), (Chen, Li, Wu, & Shen, 2017) and (Yao, et al., 2017) to propose a novel paired computational model. The original tourist arrival data is explicitly decomposed by the low-pass Hodrick-Prescott filter, wavelet transformation and a simple moving average method subject to the stationarity and seasonality of the seasonal component, which is therefore guaranteed to be a stationary seasonal process. The trend component is then obtained by subtracting the seasonal process from the original tourism series. Two separated three-layer autoregressive neural network are then estimated by the trend and seasonal component data respectively. The outputs of the two autoregressive neural networks are then aggregated as the final forecasting result of the tourism series. The three models are termed as paired Neural Network with HP filter (pNN-HP), paired Neural network with Wavelet Transformation (pNN-WT) and with Moving Average (pNN-MA). The models were thoroughly evaluated using the tourist arrival data to US from top 12 source markets up to 18 forecasting horizons. The out-of-sample forecasting results of pNN type models consistently and significantly outperform the traditional ARIMA, ARFIMA, and SARIMA model.

Previous studies of tourism arrival forecasting show that incorporating macro-economic data, i.e., FX rate, GDP growth rate, consumer price index (CPI), and others, into the model may increase the forecasting accuracy. This has not been thoroughly studied in computational models. One of the future directions may investigate the impact of incorporating such macro-economic factors into our proposed method as an exogenous feature for either trend or seasonal component modelling. Another future direction may fall in the optimal public resource allocation according to the forecasted tourist arrival. Further investigation may also consider using the pNN model in other areas which can also be observed with trend and oscillation components.

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Appendix

Appendix Table 1 This table shows the accuracy of monthly forecasts of US tourist arrivals from **Italy**. The Absolute Percentage Error (APE) is calculated at forecasting horizon 1 to 18 months (1.5 years). The *p*NN-HP, *p*NN-WT and *p*NN-MA models are all estimated by the data from Jan 1996 to Jun 2013 (210 months).

	*p*NN HP				*p*NN WT				*p*NN MA
horizon	100	1600	3600	129600	3	4	5	6	
1	1.8834%	3.6798%	3.2606%	3.2447%	1.9165%	3.8966%	3.6859%	3.8178%	7.6585%
2	3.2969%	3.7767%	3.2925%	4.4096%	2.9805%	5.6386%	4.9472%	4.3655%	3.1673%
3	2.3359%	3.3024%	2.7045%	3.9159%	1.1998%	3.4319%	1.5650%	2.5394%	4.2601%
4	2.6379%	3.9657%	2.6882%	3.5342%	1.7236%	2.0981%	2.7083%	2.3921%	8.2053%
5	3.6337%	3.7852%	2.3624%	2.9708%	4.1219%	1.4097%	2.7324%	2.1635%	8.5099%
6	2.3655%	3.0335%	2.0080%	3.0083%	0.2408%	1.8884%	1.9412%	2.2997%	0.6997%
7	4.0520%	3.6339%	2.1511%	3.7926%	2.1551%	1.3079%	3.0249%	2.4192%	1.2377%
8	4.9458%	3.0138%	2.2946%	3.1112%	2.7041%	1.9558%	0.4935%	2.6845%	4.2999%
9	3.6619%	3.7592%	3.8218%	3.6830%	3.2888%	3.7332%	3.8716%	3.1956%	5.2757%
10	4.6232%	4.5893%	4.4245%	4.4238%	2.4133%	4.8403%	5.0526%	4.0637%	2.4378%
11	4.8412%	4.8339%	4.9444%	4.0133%	3.9004%	4.7999%	2.8913%	4.0298%	0.7851%
12	4.5472%	4.3647%	4.2717%	4.0503%	4.5972%	4.1568%	4.1227%	4.9660%	3.8852%
13	6.7218%	7.6744%	8.1897%	6.9092%	5.5422%	7.2086%	8.0285%	7.0527%	9.1671%
14	6.7769%	8.4618%	9.0115%	8.7351%	7.4677%	8.2516%	8.6577%	7.5335%	3.9136%
15	5.8563%	8.9223%	7.2624%	8.3574%	5.4409%	6.8612%	5.0276%	7.4879%	5.5098%
16	6.5142%	8.2216%	7.0357%	8.8114%	6.6759%	5.9738%	5.4662%	7.5408%	10.7518%
17	6.1728%	8.6735%	7.4877%	8.0234%	8.7274%	5.4380%	5.1129%	7.9598%	13.5064%
18	6.4737%	8.7315%	7.7047%	8.6907%	5.5002%	6.4083%	6.1162%	7.8750%	4.4339%
Average	4.5189%	5.3568%	4.7176%	5.2047%	3.9220%	4.4055%	4.1914%	4.6881%	5.4280%

Appendix Table 2 This table shows the accuracy of monthly forecasts of US tourist arrivals from **Italy**. The Absolute Percentage Error (APE) is calculated at forecasting horizon 1 to 18 months (1.5 years). The ARFIMA, ARIMA, and SARIMA models are all estimated by the data from Jan 1996 to Jun 2013 (210 months).

horizon	ARFIMA	ARIMA	SARIMA
1	4.8337%	2.9845%	3.7147%
2	7.3305%	4.0975%	4.3003%
3	9.3149%	4.8629%	3.5848%

4	10.5899%	6.2805%	4.2567%
5	11.2942%	7.3904%	4.5794%
6	12.9230%	9.8283%	3.6578%
7	13.1310%	11.5981%	4.4094%
8	17.1081%	21.0395%	5.7864%
9	20.3993%	23.2992%	7.0899%
10	21.5531%	25.4982%	7.6291%
11	24.7724%	25.8667%	7.7889%
12	30.4643%	28.6646%	8.9173%
13	30.5109%	31.4510%	11.6778%
14	30.6875%	35.5084%	12.2732%
15	71.7278%	70.0575%	18.4101%
16	73.4550%	76.5076%	19.7231%
17	76.6729%	87.5999%	21.3977%
18	78.1498%	105.2109%	22.2995%
Average	30.2732%	32.0970%	9.5276%

Appendix Table 3 This table shows the accuracy of monthly forecasts of US tourist arrivals from **Spain**. The Absolute Percentage Error (APE) is calculated at forecasting horizon 1 to 18 months (1.5 years). The *p*NN-HP, *p*NN-WT and *p*NN-MA models are all estimated by the data from Jan 1996 to Jun 2013 (210 months).

	*p*NN HP				*p*NN WT				*p*NN MA
horizon	100	1600	3600	129600	3	4	5	6	
1	3.9404%	1.8678%	3.4009%	3.2953%	0.3384%	2.9523%	5.3060%	3.2152%	11.4071%
2	0.4436%	3.5890%	3.7500%	4.8361%	2.1817%	4.0248%	4.6438%	4.1263%	3.9653%
3	2.2396%	1.5545%	1.4217%	1.7788%	2.3409%	2.4067%	1.5814%	1.6889%	2.0364%
4	2.6049%	1.9242%	1.8057%	2.2602%	2.2467%	2.9203%	2.0785%	1.5532%	6.0988%
5	1.6320%	1.6675%	1.0553%	1.2478%	3.4057%	2.7812%	2.7180%	2.3709%	7.3967%
6	2.5783%	2.5089%	2.4942%	2.2306%	2.8332%	2.5722%	2.6292%	3.6606%	1.2601%
7	2.2083%	1.8717%	1.6733%	3.4554%	3.3297%	2.2537%	1.7293%	3.2302%	1.0903%
8	4.1944%	3.9225%	3.8820%	3.8851%	4.3880%	2.0576%	3.9993%	3.4900%	3.4002%
9	3.5175%	3.3679%	3.3633%	3.1606%	2.9070%	3.2828%	3.5249%	3.6301%	6.6141%
10	3.8610%	4.2484%	4.1241%	4.5263%	4.8015%	4.1200%	4.3826%	3.8609%	5.4475%
11	3.3202%	3.4834%	3.1153%	3.2486%	4.1161%	3.4901%	3.3317%	3.8897%	2.4664%
12	3.8241%	3.8620%	3.7845%	4.6260%	4.4709%	3.9162%	4.4794%	3.8702%	6.9459%
13	7.8125%	7.5381%	8.0174%	9.2755%	5.5975%	7.1380%	8.2116%	6.6697%	14.2789%
14	7.7191%	9.1000%	7.9996%	9.8795%	7.2804%	8.9833%	9.0668%	6.9508%	3.0170%
15	5.8960%	5.9729%	5.9810%	6.2228%	5.3190%	5.9420%	6.1545%	6.1454%	6.6676%
16	6.2777%	5.8600%	5.7269%	6.9562%	6.5634%	5.9733%	6.8173%	6.4820%	6.1808%
17	5.9285%	5.7847%	5.7023%	7.2565%	6.4551%	7.1493%	6.6517%	6.3988%	9.4911%
18	6.7653%	6.4748%	6.6301%	6.7869%	7.5596%	6.4853%	6.6768%	6.1579%	5.5296%
Average	4.1535%	4.1444%	4.1071%	4.7182%	4.2297%	4.3583%	4.6657%	4.2995%	5.7385%

Appendix Table 4 This table shows the accuracy of monthly forecasts of US tourist arrivals from **Spain**. The Absolute Percentage Error (APE) is calculated at forecasting horizon 1 to 18 months (1.5 years). The ARFIMA, ARIMA, and SARIMA models are all estimated by the data from Jan 1996 to Jun 2013 (210 months).

horizon	ARFIMA	ARIMA	SARIMA
1	4.8337%	2.9845%	3.9583%
2	7.3305%	4.0975%	3.9080%
3	9.3149%	4.8629%	2.8388%
4	10.5899%	6.2805%	3.6694%
5	11.2942%	7.3904%	3.9054%
6	12.9230%	9.8283%	4.1381%
7	13.1310%	11.5981%	4.1428%
8	17.1081%	21.0395%	6.4879%
9	20.3993%	23.2992%	7.0061%
10	21.5531%	25.4982%	7.8567%
11	24.7724%	25.8667%	7.3728%
12	30.4643%	28.6646%	8.9916%
13	30.5109%	31.4510%	12.4092%
14	30.6875%	35.5084%	12.3811%
15	71.7278%	70.0575%	17.8260%
16	73.4550%	76.5076%	18.8000%
17	76.6729%	87.5999%	20.4628%
18	78.1498%	105.2109%	22.0388%
Average	30.2732%	18.7821%	8.1337%

Appendix Table 5 This table shows the accuracy of monthly forecasts of US tourist arrivals from **Korea**. The Absolute Percentage Error (APE) is calculated at forecasting horizon 1 to 18 months (1.5 years). The *p*NN-HP, *p*NN-WT and *p*NN-MA models are all estimated by the data from Jan 1996 to Jun 2013 (210 months).

	*p*NN HP				*p*NN WT				*p*NN MA
horizon	100	1600	3600	129600	3	4	5	6	
1	1.4833%	1.6130%	1.1895%	1.6361%	2.3102%	1.4467%	1.1165%	1.6372%	0.3993%
2	0.5696%	0.9445%	1.7017%	0.8949%	1.6163%	1.7240%	1.0454%	0.9446%	0.4773%
3	1.4650%	2.0983%	2.5702%	1.9674%	1.5572%	2.2340%	1.5369%	1.9706%	0.8352%
4	0.5609%	2.5090%	2.6373%	2.2324%	1.5117%	2.3183%	1.9413%	1.7774%	0.0423%
5	1.3050%	1.9494%	1.7271%	1.7468%	2.9070%	1.8633%	1.1735%	1.6621%	0.7927%
6	0.8244%	1.6610%	1.5431%	1.3776%	1.0674%	1.5622%	2.8020%	1.0367%	0.6124%
7	2.3906%	3.1946%	2.7689%	2.9404%	2.2155%	3.2558%	2.5712%	3.1541%	1.9329%
8	1.1565%	1.6484%	2.6487%	2.0991%	1.9205%	2.0579%	2.5291%	3.7531%	1.3706%
9	0.8663%	2.7252%	2.7978%	1.9899%	2.8930%	2.6903%	2.1904%	3.2426%	0.5273%
10	1.2431%	3.2697%	2.9075%	2.2776%	2.9132%	3.1042%	3.6356%	3.1967%	1.1658%
11	0.8030%	2.9149%	2.5571%	1.7552%	3.1790%	3.7770%	4.2265%	4.9459%	0.6421%
12	1.2915%	3.4126%	2.9361%	2.0615%	3.1543%	3.8737%	4.9804%	4.0803%	1.9029%
13	3.3155%	5.2322%	3.6473%	3.7505%	5.2981%	5.9454%	5.5485%	5.8815%	3.0084%
14	3.0537%	6.3055%	5.0109%	3.4733%	5.9787%	6.2012%	5.2038%	5.8713%	3.8510%
15	3.2099%	6.3286%	5.4047%	3.2177%	5.7342%	6.2115%	6.2974%	6.3826%	2.3703%

16	3.1784%	5.9957%	5.1723%	2.9024%	5.9518%	6.0867%	6.1833%	6.5323%	3.5323%
17	2.9150%	5.7295%	4.4685%	2.4927%	5.4641%	6.3350%	6.6424%	6.6361%	3.2957%
18	3.5242%	6.3926%	4.5046%	2.4698%	5.7973%	6.2832%	6.3449%	6.3185%	5.3781%
Average	1.8420%	3.5514%	3.1219%	2.2936%	3.4150%	3.7206%	3.6650%	3.8346%	1.7854%

Appendix Table 6 This table shows the accuracy of monthly forecasts of US tourist arrivals from **Korea**. The Absolute Percentage Error (APE) is calculated at forecasting horizon 1 to 18 months (1.5 years). The ARFIMA, ARIMA, and SARIMA models are all estimated by the data from Jan 1996 to Jun 2013 (210 months).

horizon	ARFIMA	ARIMA	SARIMA
1	1.0212%	40.2943%	4.9225%
2	1.1793%	45.6519%	5.1590%
3	2.7185%	48.2972%	6.1137%
4	3.6141%	49.8343%	6.2708%
5	7.3728%	59.0620%	7.4147%
6	9.1359%	59.9481%	7.4155%
7	9.6288%	60.0256%	8.5526%
8	10.2235%	60.9766%	8.2167%
9	10.3071%	72.7159%	9.3587%
10	10.6437%	75.5424%	9.9909%
11	10.7144%	76.4881%	10.1821%
12	11.2069%	82.4094%	11.0282%
13	11.3557%	95.9604%	13.5403%
14	15.5508%	99.8409%	14.5765%
15	16.5127%	101.0149%	14.7895%
16	17.0306%	102.7707%	15.0306%
17	17.2215%	103.1700%	14.9428%
18	18.9664%	106.2999%	15.6618%
Average	10.2447%	74.4613%	10.1759%

Appendix Table 7 This table shows the accuracy of monthly forecasts of US tourist arrivals from **Brazil**. The Absolute Percentage Error (APE) is calculated at forecasting horizon 1 to 18 months (1.5 years). The *p*NN-HP, *p*NN-WT and *p*NN-MA models are all estimated by the data from Jan 1996 to Jun 2013 (210 months).

	*p*NN HP				*p*NN WT				*p*NN MA
horizon	100	1600	3600	129600	3	4	5	6	
1	1.3148%	1.3157%	1.2996%	1.6014%	1.1027%	1.6325%	0.4105%	1.5342%	6.4911%
2	1.1854%	1.4568%	1.2024%	1.7146%	2.3684%	1.7444%	0.9321%	0.6227%	6.2555%
3	1.5759%	1.5058%	0.9284%	2.2031%	3.1255%	2.0195%	0.5687%	2.1947%	7.1236%
4	1.3133%	1.8015%	0.6091%	1.5763%	3.1031%	1.8940%	0.3857%	2.4193%	7.8627%
5	1.7709%	1.1799%	0.1296%	2.0603%	2.9586%	2.1028%	0.6385%	1.3198%	5.8389%
6	1.7642%	1.2354%	0.1145%	2.4207%	3.6302%	2.3235%	1.2144%	2.9056%	8.2058%
7	1.8849%	1.7822%	0.4559%	2.6932%	3.0910%	2.6384%	1.4932%	2.5594%	6.6710%
8	1.8398%	1.3467%	2.3833%	2.6229%	4.5511%	2.5843%	1.6140%	1.7579%	7.9699%
9	1.1596%	1.4412%	0.8936%	2.5452%	4.9128%	2.6003%	1.3346%	2.9001%	7.5681%
10	1.0097%	1.1508%	0.6286%	2.8015%	2.6906%	2.7733%	1.7148%	3.5923%	8.6463%
11	1.2467%	1.9779%	1.2006%	2.8034%	1.9696%	2.7593%	2.6644%	3.5457%	5.9343%

12	1.9950%	1.2839%	2.5097%	1.8182%	2.3548%	2.0013%	1.8294%	2.6868%	7.0344%
13	1.9632%	3.8194%	3.3020%	4.9486%	3.0081%	4.9490%	3.7304%	5.6887%	8.1576%
14	1.6685%	2.6262%	2.5150%	4.6405%	4.5543%	4.3311%	4.8336%	6.0538%	10.2366%
15	1.4854%	2.4558%	2.1180%	4.4165%	4.5722%	3.9915%	4.6007%	6.0185%	11.2818%
16	2.0924%	2.1158%	1.7462%	3.9444%	4.7134%	5.1480%	4.6074%	5.4903%	10.2558%
17	2.2263%	2.1411%	1.8476%	3.9080%	4.1987%	4.9432%	4.4827%	5.8068%	11.3818%
18	2.3177%	2.1855%	1.4543%	4.4550%	5.1995%	5.4667%	5.1222%	6.7383%	11.6358%
Average	1.6563%	1.8234%	1.4077%	2.9541%	3.4503%	3.1057%	2.3432%	3.5464%	8.2528%

Appendix Table 8 This table shows the accuracy of monthly forecasts of US tourist arrivals from **Brazil**. The Absolute Percentage Error (APE) is calculated at forecasting horizon 1 to 18 months (1.5 years). The ARFIMA, ARIMA, and SARIMA models are all estimated by the data from Jan 1996 to Jun 2013 (210 months).

horizon	ARFIMA	ARIMA	SARIMA
1	1.2278%	1.8161%	1.7951%
2	1.6294%	2.5810%	1.9721%
3	1.7329%	3.6132%	2.4174%
4	4.3379%	6.7773%	2.9164%
5	5.0071%	10.1477%	3.0140%
6	6.0240%	12.0452%	3.8076%
7	6.2887%	13.8791%	3.9488%
8	6.4496%	14.2311%	4.3046%
9	7.3459%	15.3354%	4.3670%
10	8.4452%	15.5091%	4.4511%
11	9.7125%	15.8001%	4.5104%
12	11.2433%	16.0689%	4.6205%
13	13.5170%	16.2644%	6.3044%
14	14.2496%	16.4207%	6.5573%
15	16.0443%	23.3100%	7.2995%
16	17.1511%	26.7056%	7.6337%
17	24.2760%	29.8989%	8.6465%
18	25.7695%	32.4431%	9.3443%
Average	10.0251%	15.1582%	4.8839%

Appendix Table 9 This table shows the accuracy of monthly forecasts of US tourist arrivals from **Germany**. The Absolute Percentage Error (APE) is calculated at forecasting horizon 1 to 18 months (1.5 years). The *p*NN-HP, *p*NN-WT and *p*NN-MA models are all estimated by the data from Jan 1996 to Jun 2013 (210 months).

	*p*NN HP				*p*NN WT				*p*NN MA
horizon	100	1600	3600	129600	3	4	5	6	
1	1.3747%	1.3963%	1.1930%	2.4732%	1.7424%	3.3753%	1.5811%	2.9906%	1.1292%
2	0.2788%	1.1002%	1.8228%	1.5029%	2.4173%	0.6718%	0.0774%	0.2353%	4.5481%
3	2.0942%	2.0028%	1.9568%	1.2903%	1.9508%	1.8382%	1.8995%	1.8291%	4.3346%
4	2.0688%	1.9966%	1.9746%	2.0009%	1.9539%	1.8514%	1.9853%	2.0091%	1.6044%
5	1.5305%	1.5750%	1.3193%	1.4305%	2.3995%	1.5504%	1.6655%	1.5738%	1.5521%
6	2.2150%	2.1550%	2.1064%	2.0691%	1.9896%	2.0011%	2.0684%	2.0218%	1.7604%
7	2.8600%	2.8856%	2.2503%	2.2092%	2.7073%	2.9193%	2.2023%	2.9231%	4.1862%

8	2.2194%	3.7543%	1.8798%	3.4148%	3.7400%	1.8699%	3.4674%	3.4452%	4.7275%
9	2.6896%	2.6714%	3.6748%	2.7512%	2.1952%	2.8959%	2.2332%	2.2801%	2.1742%
10	4.5425%	4.3224%	4.6863%	3.4350%	4.4437%	4.4285%	4.3965%	4.3622%	7.9458%
11	2.2572%	2.9785%	2.8687%	2.6026%	4.8680%	4.3558%	5.0410%	5.0801%	2.6359%
12	2.7766%	2.8904%	3.2677%	3.1058%	3.5626%	3.3756%	2.9172%	3.1653%	7.4599%
13	1.3716%	8.1055%	1.3527%	8.0117%	5.8010%	7.4439%	2.9191%	9.0719%	8.6162%
14	3.5438%	3.6720%	7.7640%	6.3288%	7.3803%	7.9645%	4.4215%	8.2972%	10.3059%
15	5.5490%	5.6997%	6.6720%	6.6839%	4.6340%	6.6862%	5.7135%	6.4690%	7.8736%
16	6.2010%	6.4751%	6.5948%	6.5131%	6.1507%	6.0853%	6.4898%	6.5767%	2.8960%
17	5.5697%	6.0234%	5.9989%	5.9879%	6.4946%	5.9463%	5.8716%	7.3149%	4.5734%
18	6.8429%	7.0628%	6.8377%	6.7239%	6.7716%	6.8786%	6.7940%	6.6479%	5.3509%
Average	3.1103%	3.7093%	3.5678%	3.8075%	3.9557%	4.0077%	3.4302%	4.2385%	4.6486%

Appendix Table 10 This table shows the accuracy of monthly forecasts of US tourist arrivals from **Germany**. The Absolute Percentage Error (APE) is calculated at forecasting horizon 1 to 18 months (1.5 years). The ARFIMA, ARIMA, and SARIMA models are all estimated by the data from Jan 1996 to Jun 2013 (210 months).

horizon	ARFIMA	ARIMA	SARIMA
1	0.3397%	3.4469%	1.9129%
2	3.4448%	6.9276%	2.0934%
3	4.8205%	4.5628%	2.5981%
4	5.0343%	7.7673%	2.7497%
5	5.3356%	5.1066%	2.2763%
6	6.4019%	5.1428%	2.7210%
7	7.1616%	2.9461%	3.2046%
8	9.6190%	6.5605%	4.0634%
9	12.9312%	86.8930%	11.2173%
10	13.3089%	8.9147%	5.8897%
11	14.1300%	11.5817%	5.3091%
12	15.5623%	13.1765%	5.5691%
13	16.4700%	22.5850%	8.3408%
14	17.0988%	49.4202%	11.4724%
15	17.2917%	14.0700%	7.9402%
16	25.2028%	32.0970%	10.1166%
17	43.4020%	49.6664%	13.3499%
18	61.3051%	69.1981%	17.3103%
Average	15.4922%	22.2257%	6.5630%

Appendix Table 11 This table shows the accuracy of monthly forecasts of US tourist arrivals from **Australia**. The Absolute Percentage Error (APE) is calculated at forecasting horizon 1 to 18 months (1.5 years). The *p*NN-HP, *p*NN-WT and *p*NN-MA models are all estimated by the data from Jan 1996 to Jun 2013 (210 months).

	*p*NN HP				*p*NN WT				*p*NN MA
horizon	100	1600	3600	129600	3	4	5	6	
1	1.9902%	1.7584%	1.3113%	1.8793%	1.8799%	1.5088%	1.3197%	1.3533%	4.2470%
2	0.7915%	3.4844%	3.3466%	1.2105%	2.2083%	1.0747%	3.2869%	1.8116%	9.0320%
3	2.2215%	1.8084%	1.3281%	1.9282%	1.6308%	2.0081%	1.8743%	1.9081%	0.0180%

4	2.0622%	1.4811%	1.2220%	1.9650%	2.0829%	2.9136%	1.9640%	1.5042%	3.1279%
5	2.2829%	1.5167%	1.4188%	2.1496%	2.2995%	2.0281%	2.2308%	2.6138%	3.0510%
6	1.2340%	1.7473%	1.3688%	1.2164%	2.5208%	2.3013%	1.2925%	2.9022%	6.3291%
7	1.7498%	1.3359%	1.1883%	2.4317%	1.6341%	2.0183%	2.2896%	2.4823%	1.4221%
8	1.5632%	1.9854%	1.7670%	2.5236%	2.1161%	2.0258%	2.0042%	2.6041%	4.7428%
9	0.7428%	1.7436%	2.6982%	1.9275%	2.5382%	3.8160%	2.9935%	2.6431%	5.9798%
10	1.8219%	1.8781%	2.5905%	3.2995%	3.5053%	3.3006%	3.2688%	4.1393%	8.7299%
11	0.7649%	2.5537%	2.3230%	2.5874%	5.1502%	4.8710%	3.2945%	4.5305%	12.3760%
12	2.1226%	2.0248%	2.7298%	3.8244%	5.0801%	5.6411%	4.3353%	4.3889%	8.6401%
13	1.0951%	2.8322%	2.0142%	3.1739%	5.6447%	5.2472%	6.3051%	4.5756%	10.4457%
14	1.1351%	3.1263%	2.9730%	1.4372%	5.4761%	6.8146%	6.6748%	6.8685%	16.9133%
15	3.2942%	2.5174%	2.0307%	5.0133%	5.7394%	6.7840%	6.9017%	6.8481%	7.0926%
16	3.0780%	2.3211%	2.8475%	4.7522%	5.4360%	6.1290%	6.4867%	6.6519%	10.8718%
17	3.8895%	2.2135%	3.0543%	4.5770%	5.6120%	6.7304%	6.2120%	6.1186%	13.2559%
18	2.7448%	2.4744%	3.1659%	4.7273%	5.6026%	6.0958%	7.2296%	7.5436%	13.1924%
Average	1.9213%	2.1557%	2.1877%	2.8124%	3.6754%	3.9616%	3.8869%	3.9715%	7.7482%

Appendix Table 12 This table shows the accuracy of monthly forecasts of US tourist arrivals from **Australia**. The Absolute Percentage Error (APE) is calculated at forecasting horizon 1 to 18 months (1.5 years). The ARFIMA, ARIMA, and SARIMA models are all estimated by the data from Jan 1996 to Jun 2013 (210 months).

horizon	ARFIMA	ARIMA	SARIMA
1	0.1630%	0.1627%	1.5976%
2	1.5407%	3.8420%	2.8754%
3	2.4711%	3.9942%	1.9264%
4	2.8186%	4.4232%	2.3241%
5	3.1204%	7.5974%	2.7554%
6	6.1417%	8.0092%	3.1876%
7	7.7945%	9.5544%	3.0819%
8	10.1134%	9.9570%	3.7639%
9	10.1771%	15.1617%	4.5838%
10	10.7876%	15.5402%	5.3511%
11	13.1222%	19.3484%	6.4474%
12	18.6795%	19.6015%	7.0062%
13	19.3294%	21.9494%	7.5102%
14	20.3376%	29.0222%	9.1617%
15	21.2042%	34.4473%	9.2612%
16	21.5191%	41.0450%	10.1035%
17	23.2741%	49.6832%	11.3291%
18	30.5076%	78.1964%	14.6800%
Average	12.3945%	20.6409%	5.9415%

Appendix Table 13 This table shows the average accuracy of monthly forecasts of US tourist arrivals from ITALY. The MAPE and RMSE are average values across all forecasted data from Aug 2013 to Sep 2017. The models are all estimated by the data from Jan 1996 to Jun 2013.

ITALY	MAPE (%)			RMSE		
Horizon	pNN-HP	pNN-MA	SARIMA	pNN-HP	pNN-MA	SARIMA
1	2.0760	2.2960	5.8267	1,475.6624	1,457.7917	125.6543
2	2.1643	2.2975	6.5535	1,666.8365	1,550.6151	616.0718
3	2.4231	2.4264	6.9084	1,771.6161	1,586.2061	1,174.8861
4	2.5114	2.4301	7.7232	1,788.0513	1,635.6921	1,445.5568
5	2.5947	2.5749	7.8176	1,813.4666	1,995.6738	1,568.5179
6	2.8404	2.5902	7.9839	1,917.3266	2,094.8811	1,692.6787
7	2.8780	2.7442	8.6795	2,044.4124	2,466.9727	2,832.3098
8	2.9147	3.3665	8.8374	2,054.7212	2,547.7043	2,967.9491
9	2.9329	3.5887	8.9095	2,074.7729	2,750.9733	3,061.8112
10	3.0640	3.6322	9.0293	2,134.1112	2,859.2173	3,497.8551
11	3.1256	3.7910	9.2291	2,418.3283	3,421.4189	4,358.8237
12	3.1793	4.1297	9.7662	2,430.2504	3,676.2009	6,895.9762
13	3.2600	4.3187	10.0474	2,433.6272	3,807.4520	7,259.1092
14	3.2896	4.4406	10.3074	2,797.2310	3,862.3840	7,367.2322
15	4.0717	4.8030	10.5094	2,917.3847	3,900.5534	7,693.2765
16	4.1003	4.9981	11.2053	3,357.8388	4,175.0139	8,148.8646
17	4.4225	5.6311	11.7831	3,897.4073	4,180.4292	8,360.5889
18	5.1484	5.9064	11.8083	4,032.1618	4,204.3810	9,958.6574

Note: MAPE is Mean Average Absolute Percentage Error; RMSE is Root Mean Square Error; pNN-HP is the paired Neural Network model with HP filter; pNN-MA is the paired Neural Network model with Moving Average as the trend filter; SARIMA is the Seasonal Autoregressive Integrated Moving Average.

Appendix Table 14 This table shows the average accuracy of monthly forecasts of US tourist arrivals from SPAIN. The MAPE and RMSE are average values across all forecasted data from Aug 2013 to Sep 2017. The models are all estimated by the data from Jan 1996 to Jul 2013.

SPAIN	MAPE (%)			RMSE		
Horizon	pNN-HP	pNN-MA	SARIMA	pNN-HP	pNN-MA	SARIMA
1	2.0620	2.0070	7.5984	1,131.2550	967.7461	433.4365
2	2.2655	2.0861	7.8965	1,159.9743	969.5743	854.8061
3	2.2796	2.1114	8.4786	1,167.8067	1,299.0070	1,055.4889
4	2.4873	2.1931	8.5875	1,306.2908	1,334.5188	1,082.1928
5	2.5127	2.2924	9.2462	1,338.3505	1,396.7860	1,330.7147
6	2.5820	2.3603	9.8384	1,371.1106	1,538.6468	2,073.4365
7	2.6814	2.6981	10.1559	1,403.6249	1,550.6383	2,444.0618
8	2.8738	2.7678	10.1704	1,469.7818	1,553.7871	2,669.5379
9	3.1616	2.7878	10.1807	1,629.6006	1,649.0506	2,816.0434
10	3.3143	3.0014	10.4074	1,682.1278	1,698.8751	3,545.6167
11	3.3900	3.8057	10.8182	1,744.6072	1,761.1165	3,605.0670
12	3.4045	3.8778	10.9827	2,063.5352	1,808.4086	4,142.6767
13	3.7876	3.8861	11.2368	2,419.1042	1,893.1316	4,225.0093
14	3.9407	3.8905	11.3642	2,725.9535	2,011.4587	4,245.9654
15	5.1572	4.0116	11.3889	2,913.4500	2,376.6354	5,092.6010
16	5.7490	4.1130	11.6754	3,181.5540	2,568.4638	5,363.5469
17	5.7636	4.1994	11.6985	3,286.3516	2,740.7787	5,946.4634
18	6.3312	4.5619	12.1358	3,287.6573	2,776.1523	6,443.4930

Note: MAPE is Mean Average Absolute Percentage Error; RMSE is Root Mean Square Error; pNN-HP is the paired Neural Network model with HP filter; pNN-MA is the paired Neural Network model with Moving Average as the trend filter; SARIMA is the Seasonal Autoregressive Integrated Moving Average.

Appendix Table 15 This table shows the average accuracy of monthly forecasts of US tourist arrivals from KOREA. The MAPE and RMSE are average values across all forecasted data from Aug 2013 to Sep 2017. The models are all estimated by the data from Jan 1996 to Jul 2013.

KOREA	MAPE (%)			RMSE		
Horizon	pNN-HP	pNN-MA	SARIMA	pNN-HP	pNN-MA	SARIMA
1	2.0793	2.1199	6.3157	2,640.2352	3,046.9965	1,076.3064
2	2.1052	3.8615	7.8786	2,952.5378	4,879.4001	3,555.9646
3	2.1470	4.1527	9.9998	3,085.8545	4,984.1086	3,593.8022
4	2.2451	4.2305	10.2241	3,086.3512	5,002.5364	4,073.1923
5	2.4745	4.2319	10.6832	3,471.6760	5,128.7030	6,417.4305
6	3.0370	4.6459	10.8793	3,804.4224	5,592.8176	6,577.5964
7	3.6132	4.7867	10.8827	4,032.4997	6,136.6385	7,526.4953
8	3.7898	5.2997	12.2962	4,650.4786	6,279.4104	10,987.4539
9	3.8106	7.5102	13.1233	5,191.7739	9,398.1144	13,322.1902
10	3.8585	7.5286	13.2552	5,511.4165	9,484.0720	13,774.7276
11	3.8876	8.4528	14.4313	5,819.9610	10,094.5358	21,796.1997
12	3.9205	9.0589	14.9495	5,879.5808	10,315.7880	25,144.5286
13	3.9252	9.1615	15.7532	6,364.2125	13,809.4776	25,911.6304
14	4.0039	9.3973	15.9212	6,407.3150	14,805.1213	26,315.7580
15	4.3950	9.9553	16.5303	6,593.0796	16,049.2606	28,834.7197
16	4.6872	10.4615	16.7469	6,869.8729	16,449.2499	32,216.6823
17	5.0658	10.6986	17.9139	7,006.9979	16,760.7544	36,164.1563
18	5.6340	10.7651	18.4079	8,701.1004	17,084.5424	36,280.4084

Note: MAPE is Mean Average Absolute Percentage Error; RMSE is Root Mean Square Error; pNN-HP is the paired Neural Network model with HP filter; pNN-MA is the paired Neural Network model with Moving Average as the trend filter; SARIMA is the Seasonal Autoregressive Integrated Moving Average.

Appendix Table 16 This table shows the average accuracy of monthly forecasts of US tourist arrivals from BRAZIL. The MAPE and RMSE are average values across all forecasted data from Aug 2013 to Sep 2017. The models are all estimated by the data from Jan 1996 to Jul 2013.

BRAZIL	MAPE (%)			RMSE		
Horizon	pNN-HP	pNN-MA	SARIMA	pNN-HP	pNN-MA	SARIMA
1	2.2335	2.5098	6.4360	3,057.5383	4,257.6484	2,045.6188
2	2.6828	3.1460	7.2434	3,392.3893	5,259.9389	7,878.5647
3	2.7026	3.1878	8.0854	3,521.7652	5,283.6159	8,763.6322
4	2.8603	3.4739	8.1748	4,420.9312	5,399.7015	13,016.4555
5	2.8874	3.6534	8.8473	4,506.7629	5,406.3148	15,660.7052
6	2.9132	3.7979	9.6939	4,537.9710	5,574.7851	15,943.6963
7	2.9218	3.8081	9.9693	4,545.9499	5,634.5468	16,920.2905
8	2.9962	3.8916	10.1870	4,863.4487	5,654.2005	20,694.9382
9	3.0359	4.1216	10.2380	4,935.2503	6,305.7624	22,745.5311
10	3.0871	4.5922	11.1329	5,222.5648	6,567.7108	22,793.9771
11	3.1031	4.6884	11.3045	6,409.7712	6,625.3523	25,452.6020
12	3.2811	4.7335	11.9521	6,524.7034	6,719.7297	26,467.4362
13	3.3392	5.0993	12.8084	6,857.0126	6,893.2053	26,535.0114
14	4.6565	5.1042	13.3779	7,413.8218	6,911.0253	28,440.4143
15	5.0524	5.1769	13.7426	7,822.6411	7,187.5633	29,432.2708
16	5.3771	5.3796	13.7932	9,764.8979	8,337.4461	30,144.2447
17	6.0188	5.4892	13.8172	10,977.9553	8,693.2951	30,384.7618
18	8.5497	5.7705	14.2168	15,743.3030	8,827.6983	31,155.7587

Note: MAPE is Mean Average Absolute Percentage Error; RMSE is Root Mean Square Error; pNN-HP is the paired Neural Network model with HP filter; pNN-MA is the paired Neural Network model with Moving Average as the trend filter; SARIMA is the Seasonal Autoregressive Integrated Moving Average.

Appendix Table 17 This table shows the average accuracy of monthly forecasts of US tourist arrivals from GERMANY. The MAPE and RMSE are average values across all forecasted data from Aug 2013 to Sep 2017. The models are all estimated by the data from Jan 1996 to Jul 2013.

GERMANY	MAPE (%)			RMSE		
Horizon	pNN-HP	pNN-MA	SARIMA	pNN-HP	pNN-MA	SARIMA
1	2.0232	2.0899	6.0737	2,886.2685	2,814.0082	17.0417
2	2.0819	2.0990	7.0777	3,355.7972	3,240.0784	481.5342
3	2.0951	2.1730	7.1654	3,677.2995	3,761.6868	2,754.1544
4	2.0962	2.2608	8.3062	3,690.3158	4,086.0665	4,853.5575
5	2.2106	2.2732	9.0259	4,077.4593	4,089.7474	5,529.2361
6	2.2189	2.2953	9.3118	4,082.0890	4,112.9655	8,141.9160
7	2.3521	2.2956	9.8658	4,176.1337	4,213.4900	8,243.8132
8	2.3563	2.3728	10.0324	4,251.6155	4,736.7540	9,294.0308
9	2.3769	2.5377	10.2361	4,350.0382	5,049.1387	10,224.6293
10	2.3779	2.6588	10.2936	4,417.1725	5,282.7154	12,388.9522
11	2.4945	2.7320	10.5710	4,695.4755	5,571.7511	12,506.2165
12	2.6526	2.8772	10.9605	4,968.6968	5,641.2513	14,158.8806
13	2.9490	2.9504	11.5012	4,992.0286	6,083.6366	15,079.0906
14	3.0304	3.1776	11.7935	5,167.5828	6,146.0525	15,180.6853
15	3.1270	3.3762	11.9868	5,358.2740	6,291.6163	15,260.8974
16	3.2708	3.5396	11.9950	6,048.0195	6,560.1257	15,562.5985
17	3.6697	3.9830	12.4405	6,385.2877	6,812.1865	17,830.4787
18	3.7681	4.0417	12.8322	6,582.6340	6,880.3405	18,372.8446

Note: MAPE is Mean Average Absolute Percentage Error; RMSE is Root Mean Square Error; pNN-HP is the paired Neural Network model with HP filter; pNN-MA is the paired Neural Network model with Moving Average as the trend filter; SARIMA is the Seasonal Autoregressive Integrated Moving Average.

Appendix Table 18 This table shows the average accuracy of monthly forecasts of US tourist arrivals from AUSTRALIA. The MAPE and RMSE are average values across all forecasted data from Aug 2013 to Sep 2017. The models are all estimated by the data from Jan 1996 to Jul 2013.

AUSTRALIA	MAPE (%)			RMSE		
Horizon	pNN-HP	pNN-MA	SARIMA	pNN-HP	pNN-MA	SARIMA
1	2.0344	2.0963	5.8563	1,879.6087	2,203.7164	115.8073
2	2.0633	2.1058	6.5257	1,976.2163	2,296.9482	843.5682
3	2.1108	2.1105	7.3650	2,335.8330	2,487.9154	1,094.8731
4	2.1143	2.3146	7.3873	2,403.0227	2,708.4169	1,429.3211
5	2.1586	2.3347	7.3945	2,430.1701	3,024.3907	1,710.1054
6	2.2065	2.3538	7.6419	2,655.8755	3,136.8702	1,911.4456
7	2.2764	2.4584	7.9794	2,796.2365	3,148.3399	2,134.2615
8	2.4465	2.7246	8.0472	2,823.3480	3,432.0916	2,150.8918
9	2.6196	2.7901	8.7539	3,073.6260	3,888.0412	3,084.2868
10	2.6956	3.7065	8.9697	3,134.7780	4,331.6185	3,436.5370
11	2.7121	3.8835	9.0382	3,500.6858	4,414.2942	3,587.8382
12	2.7825	5.0907	9.1288	3,564.7621	5,335.7646	3,841.6217
13	3.1559	5.4759	9.3118	3,854.4347	5,855.3615	4,474.2256
14	3.2456	5.5153	9.6002	3,870.5337	6,026.6730	4,694.3326
15	3.4178	5.7663	9.6531	3,953.1031	6,466.3063	5,541.1998
16	3.4516	6.1835	9.9969	3,970.5294	6,522.8144	5,627.8470
17	3.7459	6.7793	10.1529	4,335.7868	7,241.5357	5,801.2891
18	3.9772	6.7820	10.3305	4,429.4164	7,442.9502	6,843.4489

Note: MAPE is Mean Average Absolute Percentage Error; RMSE is Root Mean Square Error; pNN-HP is the paired Neural Network model with HP filter; pNN-MA is the paired Neural Network model with Moving Average as the trend filter; SARIMA is the Seasonal Autoregressive Integrated Moving Average.

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